DETECTING PLANT DISEASES USING DEEP LEARNING ARCHITECTURES

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Abstract
The technological advancements in artificial intelligence enabled the usage of complex mathematical models in various fields, such as agriculture. Not long ago, the only method of detecting certain abnormalities in the development of a plant was the trained eye of an expert. Today, we can make use of deep learning techniques to precisely identify these problems. For a multitude of crops, the abnormalities in the development of the plant can be identified by carefully analyzing the health of the leaves. In this paper, we make use of a public leaf disease dataset to identify 2 different diseases commonly found on potato leaves, namely the early blight and the late blight. Using GoogLeNet's Inception-v3 convolutional neural network (CNN) architecture, we trained the model using a total of 6456 images, of which 456 were depicting healthy leaves. 5166 images were used for training, while 1290 were used for validation. The network was trained 3 times, using fully colored, grayscale and segmented images. The achieved overall accuracy range between 93.48% for grayscale images and 97.67% for segmented images.

Keywords:
Convolutional Neural Networks, potato leaf diseases, Inception-v3, Deep learning

JEL classification:
Q10, Q16

Introduction

With the continuous increase of the world's population, the need of sustainable food sources is greater than ever. The overall health of crops has a major impact on the world economics, as loses in food production due to diseases can sum up to important amounts. Nowadays, the potato *(Solanum Tuberosum)* is one of the most cultivated vegetables in the world. With its origins in South America, the potato is cultivated worldwide, the total world production in 2018 being of 458.490.361 metric tons. China, India, Ukraine, Russian Federation and USA are the biggest potatoes producers. In 2018, Romania produced a quantity of 3.022.758 tons of potatoes, being ranked 10th in Europe and 25th in the world. It is also the 4th most important crop in the country, after maize, wheat and sunflower. The total surface of land cultivated with potatoes was 173.296 ha (FAOSTAT, 2020). However, an important amount of these crops is lost due to inadequate farming procedures, dysfunctional cultivation practices and the increasing number of diseases that are affecting the potato plant leaves.

Not long ago, the only way of identifying a disease in a plant was the trained eye of an experienced farmer. However, this process was not very efficient, the manual process requiring a lot of time and knowledge. Plant pathologists were needed to properly classify these diseases. Also, an important role in the proper development of the crops is represented by a predictable and suitable climate for the development of the cultivated plants. However, the climate conditions are changing drastically year over year, with prolonged periods of drough, as well as heavy rains and storms, destroying large areas of cultivated fields. (Istudor et al., 2019). Today, computer-aided systems can automate this process by scrutinizing the visual symptoms and categorizing diseases. Early identification of abnormalities in plant development contributes significantly to the increase of the potato production, both qualitative and quantitative, as well as preventing the disease outbreaks. (Bazgă, Olteanu and Chira, 2019). Still, most of the Romanian young farmers with lower incomes are percieving technological advancement in the agricultural field as a threat to the development of their businesses, since the traditional methods they apply are less expensive. (Cristea et al., 2019).

This study focuses on detecting and classifying potato leaf diseases based on the visual patterns and symptoms specific for each disease, using advanced computer vision techniques, like convolutional neural networks. While there are a multitude of pathogens that can cause diseases in the potato crops, this study focuses only on early blight, as well as late blight, the only limitation being the data that could be acquired. Further extensions to the present study are possible, given the availability of meaningful data to feed the proposed model.

Early blight

Early blight is a fungal disease caused by *Alternaria solani* pathogen, commonly found in tomato and potato crops. Despite its name, the early blight develops usually on mature foliage. Left uncontrolled, the disease can lead to complete defoliation of the plant.

Alternaria solani is a fungus that is naturally present in the fields where potato has been grown. It resides both in the soil, as well as in the plant’s stem or leaves. The spores are easily carried by air currents, splashing rain or even irrigation water. It develops quite fast in the mid-season, under warm, humid weather conditions and spreads even faster when plants are lacking proper nutrition or are affected by other pests or drought.

On potato, the disease is characterized by small, dark brown or black and irregular lesions, ranging in size up to 1.5cm. On larger lesions, a concentric pattern can be observed. When the lesions are numerous, they may grow together, causing the leaves to turn yellow and die. (UMASS, 2013)

Late blight

Late blight, also known as potato blight, is a disease caused by *Phytophthora infestans*, a eukaryotic microorganism found mostly in moist and warm environments. Usually, the disease develops on the lower foliage of the plant, as well as on the tubers. The full lifecycle of the fungus can be completed in as short as 5 days.

Originating from Mexico, late blight is responsible for the death by starvation of over one million people in Ireland between 1845 and 1852. Also, during the First World War, due to the lack of copper sulfate on the market led to a new late blight outbreak, 700.000 German civilians dying from starvation. (Njoroge et al., 2019)

At leaf level, the disease can be identified by the large, dark brown blotches with a green edge. In high humidity conditions, the leaves are covered with a thin, powdery white fungal coat. (UMASS, 2013)

Fig. no. 1 shows the visual symptoms of potato leaves affected by *Alternaria solani* and *Phytophthora infestans*.

Fig. no. 1 Potato leaves infected with Alternaria solani (left) and Phytophthora infestans (right)

The dataset

The image dataset used for this paper is provided as a Git repository (Github, 2018) known as PlantVillage Dataset. From this image collection, only the images depicting potato leaves, both healthy and ill, are selected. The images are grouped into 3 categories: colored, grayscale and segmented. The segmented images are part of the dataset itself, depicting the same color image, but with the background removed. In this way, we improved the quality of training, eliminating unnecessary noise from the images. Figure 2 shows the same leaf into these 3 different states.

Fig. no. 2. Leaf infected with Alternaria solani: fully colored (left), grayscale (center), segmented (right)

There are 2152 images in each category: 152 images of healthy leaves, 1000 images of leaves infected with early blight, while other 1000 images represent leaves infected with late blight. The total number of 6456 images are used. The dataset is split into training and testing images, using an 80%-20% ratio, as shown in Table 1. The images are stored as JPG files, having a resolution of 256x256 pixels.

Table no. 1 Distribution of images in the dataset

Type	Healthy		Early blight		Late blight		TOTAL
	Training	Test	Training	Test	Training	Test	
Colored	122	30	800	200	800	200	2152
Grayscale	122	30	800	200	800	200	2152
Segmented	122	30	800	200	800	200	2152

GoogLeNet Inception-v3

For the proposed paper, we used the GoogLeNet deep convolutional neural network architecture, codenamed Inception. Being the winner of ILSVRC (ImageNet Large Scale Visual Recognition Competition) in 2014, Inception-v1 used a deeper model than its principal competitors, AlexNet, ZFNet and VGGNet. In 2015, the overall architecture was redesigned, as described in Table 2, being the 3rd version of GoogleNet's CNN. (Szegedy et al., 2015)

The network architecture of GoogLeNet versions are different from VGGNet, ZFNet and AlexNet. GoogLeNet uses a technique called inception module, which consists into different sizes of convolutions for the same input, while stacking all the outputs. For this reason, it uses a lot less parameters than previous architectures, while increasing the accuracy of the predictions. (Szegedy et al., 2015)

Table no. 2 Inception-v3 architecture details

Parameter	Inception-v3
Number of operations	12 million
Convolution filter size	1x1, 3x3 – previous 5x5 filters in Inception-v1 were replaced with two 3x3 filters
Layers	42
Auxiliary classifiers	1
Top accuracy	78.8%
Speed	With 42 layers deep, it's only 2.5 slower than the 22-layer architecture of Inception-v1 and much faster than VGGNet

Source: Jahanadad, S. et al, 2015

Training methodology

The architecture described in Figure 3 was coded using C#, ML.NET and TensorFlow.NET, the Microsoft implementation over Google's Deep Learning System, TensorFlow. The development and testing were performed on a local machine, featuring an Intel® Core™ i5-4330 CPU, 16GB DDR3 2133MHz RAM and a 2.5" SATA III 1TB SSD.

The project refers to the design and implementation of an offline leaf disease classification system that can classify images of potato leaves into 3 categories: healthy, infected with early blight and infected with late blight. The dataset is labeled using regular file processing with C#, resulting into two CSV files, containing the filename and the class for each image. Then, the dataset is fed into CNN architecture Inception-v3, using L-BFSG (Limited-memory Broyden-Fletcher-Goldfarb-Shanno) maximum entropy algorithm as the trainer for multiclass classification.

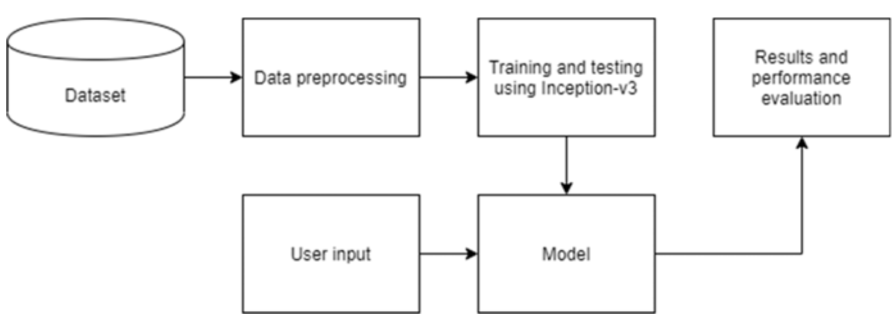

Fig. no. 3 Model diagram of the proposed system

The code below explains how the Inception-v3 pipeline was configured, as well as the process of training and evaluating the resulting model.
First of all, we created a pipeline that will run all the steps sequentially, then set the data source for the pipeline with our local path. After that, we resized the images to the required size of 224x224 pixels and fed them to the Inception model.

```
MLContext mlContext = new MLContext();
IEstimator<ITransformer> pipeline =
       mlContext.Transforms.LoadImages(outputColumnName: "input",
              imageFolder: _imagesFolder, inputColumnName:
              nameof(ImageData.ImagePath))
       .Append(mlContext.Transforms.ResizeImages(
              outputColumnName: "input",
              imageWidth: InceptionSettings.ImageWidth,
              imageHeight: InceptionSettings.ImageHeight,
              inputColumnName: "input"))
       .Append(mlContext.Transforms.ExtractPixels(
              outputColumnName: "input",
              interleavePixelColors: InceptionSettings.ChannelsLast, offsetImage:
              InceptionSettings.Mean))
       .Append(mlContext.Model.LoadTensorFlowModel(
              _inceptionTensorFlowModel)
      .ScoreTensorFlowModel(
              outputColumnNames: new[] { "softmax2_pre_activation" },
              inputColumnNames: new[] { "input" }, addBatchDimensionInput: true))
```

We then mapped the CSV field storing the label for each image to the classes that the model will use to classify the input. As activation function, we used the LBFGS maximum entropy algorithm.

```
pipeline.Append(mlContext.Transforms.Conversion.MapValueToKey(
              outputColumnName: "LabelKey",
              inputColumnName: "Label"))
       .Append(mlContext.MulticlassClassification.Trainers
              .LbfgsMaximumEntropy(
                     labelColumnName: "LabelKey",
                     featureColumnName: "softmax2_pre_activation"))
       .Append(mlContext.Transforms.Conversion
              .MapKeyToValue("PredictedLabelValue","PredictedLabel"))
       .AppendCacheCheckpoint(mlContext);
IDataView trainingData = mlContext.Data.LoadFromEnumerable<ImageData>(
       ReadFromCsv(_trainTagsCsv, _imagesFolder));
```

In the end, we started the training process of the model and generated the predictions.

```
ITransformer model = pipeline.Fit(trainingData);
IDataView testData =
       mlContext.Data.LoadFromEnumerable<ImageData>(
              ReadFromCsv(_testTagsCsv, _imagesFolder));
IDataView predictions = model.Transform(testData);
IEnumerable<ImagePrediction> imagePredictionData =
       mlContext.Data.CreateEnumerable<ImagePrediction>(
              predictions, true);
MulticlassClassificationMetrics metrics =
       mlContext.MulticlassClassification.Evaluate(
       predictions,
       labelColumnName: "LabelKey",
       predictedLabelColumnName: "PredictedLabel");
```

Accuracy validation

Table 3 shows the results obtained from training the Inception-v3 CNN on the 3 types of images. The dataset size was identical for all 3 processes, containing 2152 images, sized 256x256 pixels. Figure 4 shows the comparison between the results obtained for the processes.

Table no. 3 Experimental results for healthy (H), early blight infected (EB) and late blight infected (LB) leaves

Set	Disease	Dataset		Results				Accuracy (%)	Log loss	Compute time (seconds)
		Training	Test	Correct	Incorrect, predicted as					
					H	EB	LB			
Color	H.	122	30	25	-	0	5	97.20	0.0727	116.12
	E.B	800	200	198	0	-	2			
	L.B.	800	200	195	3	2	-			
	TOTAL	**1722**	**430**	**418**	**3**	**2**	**7**			
Segmented	H	122	30	27	-	0	3	97.67	0.0624	121.47
	E.B.	800	200	199	0	-	1			
	L.B	800	200	194	4	2	-			
	TOTAL	**1722**	**430**	**420**	**4**	**2**	**4**			
Grayscale	H.	122	30	20	-	0	10	93.48	0.211	118.55
	E.B.	800	200	197	0	-	3			
	L.B.	800	200	185	7	8	-			
	TOTAL	**1722**	**430**	**402**	**7**	**8**	**13**			

Inception-v3 performed the best in the case of segmented images, the overall accuracy being of 97.67%. On the other side, the lowest performance was recorded on the grayscale images, the overall accuracy being of 93.47%, while the log loss raised up to 0.211. The computation time for each category is comparable.

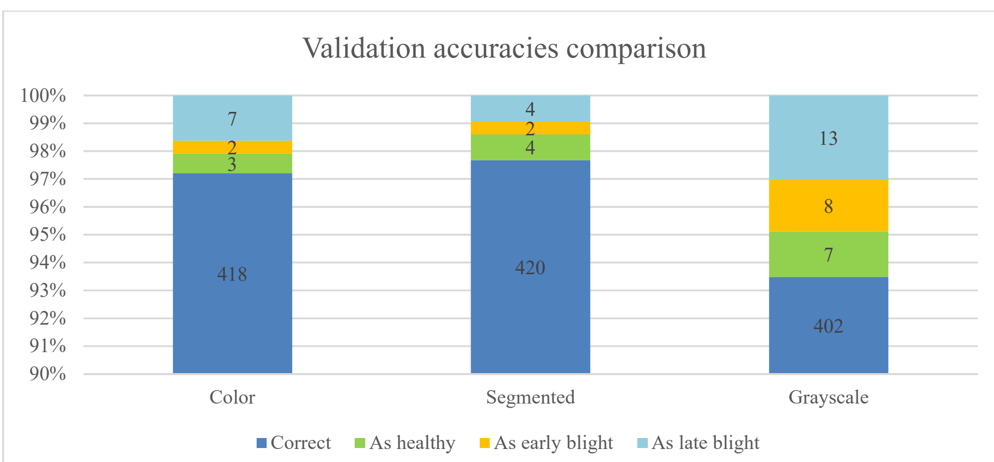

Fig. no. 4. Comparison between incorrect results on different types of images

Conclusions

Nowadays, the ongoing expansion of agricultural activities due to the constant increase in population requires new methods of making the crops monitoring easier and more effective. The lack of skilled workforce, the large areas of land that needs monitoring and the sanitary crysis that the world is facing today, which forces the workers to apply strict security norms are making this process even more difficult.

This paper proposes a classifier system based on GoogLeNet's Convolutional Neural Network architecture Inception-v3 to identify the existence of 2 main potato crops diseases, the early blight and the late blight. The development of the system was made on a local machine, using C#, ML.NET and TensorFlow.NET. The L-BFGS maximum entropy algorithm was used as the trainer function.

A total number of 6456 images were used to train 3 different models, comparing the results obtained by different means of preprocessing the data. The best outcome was obtained using images that had the background removed, while keeping the RGB channels intact, with an accuracy score of 97.67%. On the opposite end, grayscale images resulted in the least performance, the results being, however, satisfactory, with an accuracy score of 93.48%.

Further improvements guided by this work are to use different trainer functions, like SDCA (Stochastic Dual Coordinate Ascent) maximum entropy algorithm, OvA (one-versus-all) or Naïve Bayes. Furthermore, more advanced CNN architectures like Inception-v4 or Inception-ResNet may be used to increase the overall performance. Finally, more images can be added to the current dataset, expanding the range of diseases identifiable by the system.

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