A classic approach to detect potato diseases

Agriculture is the set of techniques and knowledge to cultivate the land, and is part of the primary production sector. Hence, improving agriculture production is crucial for our survival. For example, some time ago, in the United States a farmer was needed to feed 2 to 5 people, while today, thanks to technology, a farmer can feed 130 people [Wiki, 2001]. Thecnology can be used for early detection through computer vision techniques and help to minimize crop losses of different plant such as potatoes, beans, rice, etc Nowadays,the harvest of potatoes is estimated a 14 % [Per, 2006] of losses considered the annual production of 100 x 10^6 tons [FAO, 2018] due to the infestation of pests. Traditionally, human specialists detect these anomalies, but this process is time-consuming and susceptible to error due to human fatigue. We aim to automate this process to reduce time processing and cost. Additionally, we want to provide automatic early detection. Thus once the pest is detected, the necessary measures can be taken to save the crops

There are works where classifies if the fruit is mature or immature, for example, which evaluates if an apple is ripe [Murrugarra, 2012],likewise there are related works to the detection of diseases and quality control in apples [J.Woodford *et al.*, 1999] or olives [Carranza and Murrugarra, 2007], these approaches receive as input a photo of the fruit. This does not apply to our case given the characteristics of a tuber, instead our approach receives a photo of a potato leaf.

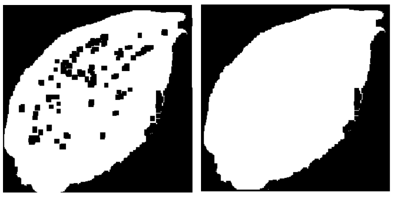
For the purposes of this project, the images were separated into 3 groups: Images of potato leaves in good condition, potato leaves affected by Phytophthora infestans [Fry, 2008], potato leaves affected by Alternaria Solaris [THOMMA, 2003], these images were obtained from Plant village dataset. A sample of three leaves is shown in Figure 1. All images are in RGB format with dimensions of 256x256. There are 152 leaves in good conditions, 152 leaves affected by Phytophthora infestans and 152 leaves affected by Alternaria Solari.

(a) leaf in good condition (b) leaf affected by Alternaria Solaris (c) leaf affected by Phytopthora infestans

Figure 1: *Types of leaf in Plant village dataset [PlanTVillage, 2015]. The leaf on the left side is in good condition, while the leaves on the right side have a disease.*

Our goal is to automatically detect pests in potato from an image of its leaves. Our methodology is composed of the following steps:

- **Data preparation**: In order to improve our performance, we increase our dataset size using the following transformations: rotations, turns, and reflections. Thus, the data is split in 60% for training, 20% for validation, and 20% for test. To ensure that all classes have the same distribution, we apply a stratified partition.
- **Segmentation**: This procedure serve to focus in damaged regions of leaves. For example, Figure 3 show the process how to focus on damaged regions (brown color).
  - **Segmentation of the leaf with the background** We work in the HSV color space after the Otsu algorithm was applied [Otsu, 1979] to obtain a threshold and binarize the image. Then, we apply morphological operations to soften the image such as dilatation and erosion generating Figure 2 (a). Then, we remove holes in the image applying dilatation operations with a matrix of zeros with a padding of 1 generating Figure 2 (b).
  - **Segmentation of the unaffected parts of the sheet:** We work in the color space l*a*b* because is easy to extract the green color. Values lower than 0 in a* channel detect green color.



(a) Mask with holes (b) Mask without holes after morphological operations

Figure 2: *Results of the first phase of the segmentation.*

(a) Segmentation of leaf with the background (b) Segmentation of the parts not affected of the leaf (c) Final Segmentation of affected part

Figure 3: *Results of each part of the segmentation.*

- **Feature extraction**: We extract 9 features of the resulting image such as: contrast, correlation, energy, homogeneity, mean, standard deviation, entropy, contrast, and skewness. All features are represented by one scalar value.
- **Classifier evaluation**: We compare four different classifiers: five nearest neighbour, support vector machines with a rbf kernel, logistic regression with l2 regularization and lbfgs optimizer and an MLP neural network. We worked with a neuronal network with 9 neurons in the input layer, 5 neurons in the hidden layer, 3 neurons in the output layer with the backpropagation algorithm [Rumelhart *et al.*, 1986] with Adam optimizer [Kingma and Ba, 2015], Relu activation function, and randomized weights.

  We compare these methods with accuracy because the data is balanced. Results are shown in Table 1.

	MLP	5-KNN	SVM	Log. Reg.
Accuracy	94.7%	91.7%	**96.3%**	93.4%

Table 1: *Metrics in the validation data. Best results are highlighted in* ***bold*** *per row.*

We want to deeply understand our results. Thus, we visualize our features. We apply Principal Component Analysis (PCA) [Pearson, 1901]) for a better understanding of our feature space on Figure 4.

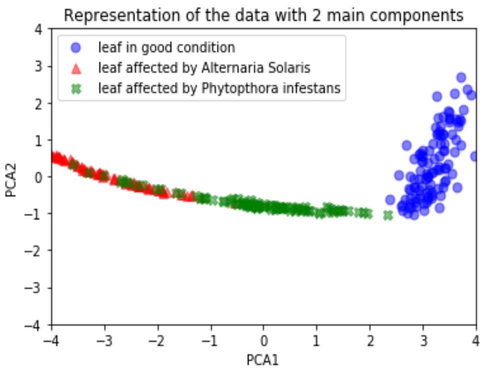


Figure 4: *PCA visualization of our data using two components.*

We find that two main components obtain 96% of representativeness of the data. Also, we observe that Class 1 (Potato in good condition) is linearly separable from the other 2 classes. Also, the other two classes present low overlap. Considering these two facts, we observed that our classes are easy to separate, which ensures high performance.

In future work, we plan to use deep learning to find better feature representation and compare with traditional methods. We expect that deep learning methods can provide even better performance. Also, we plan to expand this algorithm for a wider variety of pests and other plants. We can focus on plants that have a high rate of losses by pests. Some examples are rice, wheat, corn, soybeans, and cotton.

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