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Evaluation of Image Segmentation Algorithms for Plant Disease Detection

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Abstract: Processing images efficiently may be influenced by some important factors which are the techniques chosen, the field of study and the quality of images. In this work, we study the field of agriculture with the focus on the early detection of plant diseases through image processing. To detect plant diseases such bacterial diseases, fungal diseases and virus, two main techniques exist: The traditional techniques provided by agricultural experts during visit on the field and the artificial techniques based on images processing algorithms. Since plantations are usually distant from the cities where experts are not easy to find, the artificial techniques incorporated in computer programs become suitable. The modern techniques used to analyse images rely on existing algorithms such as k-nearest neighbor, k-means clustering, fuzzy logic, genetic algorithm, neural networks, etc. Five main phases characterise the process of images analysis: image acquisition, pre-treatment, segmentation, feature extraction and classification. Amongst these phases, we particularly focus on the segmentation which allows locating portions of leaf that are affected by a disease. Doing so, in this paper we propose a method to evaluate segmentation algorithms (k-means clustering, canny edge and k-nearest neighbor) on the diagnostic of diseases of three of the most cultivated plants (corn, potato, tomato) in the region of study. We study and compare performance values using the ROC-AUC of disease classification using the Support Vector Machine (SVM) algorithm. The obtained results show that the canny edge algorithm produces very poor performances on the family of solanaceae plants including potato. The k-nearest neighbour algorithm produces very poor performance due to the difficulty of choosing the k-value. Finally, the k-means algorithm makes it possible to obtain good prediction rates on all the chosen plants.

Index Terms: Image processing, image segmentation, plant disease, plant disease classification

1. Introduction

The economy of many countries depends largely on agriculture. It is also the case of Cameroon with the economy dependence of up to 76, 38 % based on agriculture. But the agricultural activities are facing diverse challenges. Due the climate changes and some other reasons such as insect attacks, plants are subject to many diseases which destroys plant leaves, fruits, trunks and roots. Many techniques exist for plant disease detection namely: traditional techniques and modern techniques. In order to apply the modern techniques, we use the approaches of image processing and machine learning to diagnose plant diseases. The process of detecting plant disease focusing on image segmentation include different phase: image acquisition, image pre-processing, image segmentation, feature extraction and classification. One of the key phases is the image segmentation.

The image segmentation is the process which consists to divide an image into regions, sub regions or objects with the same characteristics. The discontinuity and the similarity are the two main properties used to process image segmentation. Based on these properties, the image segmentation is categorised as edged-based segmentation and region-based segmentation [1].

Many researches have been conducted for plant disease detection using different segmentation algorithms [6, 7, 8, 9, 10, 11] but less work is done aiming to compare the disease prediction result based on the type of image segmentation algorithms and the type of plant. So, it is difficult to know how to choose the best segmentation algorithms according to the type of plant.

The main objective of this research is to assess the disease prediction based on the choice of the segmentation algorithm and the plant. In this work, we evaluate the impact of three main segmentation algorithms (k-means clustering, canny edge and k-nearest neighbour) for the detection of diseases of three plants which are corn, potatoes and tomatoes. Those plants belong to the most grown in the region of our case study, i.e. the Adamawa region in Cameroon.

The present paper is organised in five main sections. After the introductory section, the second one presents some generalities on plant disease detection using image processing, the third section deals with our methodology, our findings are presented in the fourth section and an overall conclusion is drawn in the fifth section.

2. Reviewing some Generalities on Image Processing

Dealing with image segmentation is a difficult issue in the field of image analysis using computer systems. Plant disease detection is one of the various applications of image segmentation. In this section, we revise the existing image segmentation methods and we also focus on some basic principles of the process of automatic detection of plant diseases.

2.1. Reviewing some generalities on image processing

In fact, image analysis is used in various domains to solve diverse problems. For instance, fingerprint in the field of security, medical imagery, objects in satellite images, detection of plant disease and so on [1]. It consists of five main phases: image acquisition, image pre-processing or pre-treatment, image segmentation, feature segmentation and classification [2]. Those phases are resumed in Fig.1. for automatic plant disease detection.

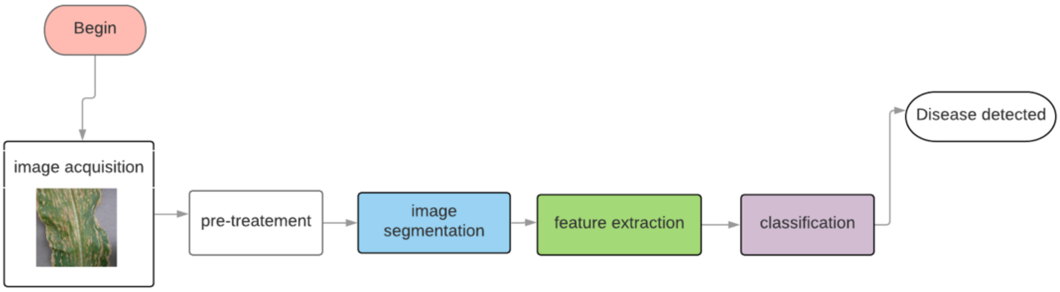


Fig.1. Main steps of automatic plant disease diagnostic

- The **image acquisition** consists to acquire images of the part of the plant which is affected by diseases using a digital camera.
- The **image pre-processing** or **pre-treatment** aims to improve the quality of the captured images and also to remove existing noises. The operations carry out here are the re-dimension, the contrast improvement etc.
- The **image segmentation** is considered as the most important step. It consists to divide the image in different regions, pixels of different parts with the same characteristics.
- The **feature extraction** aims to compute some image features in order to classify them. The most implemented method is the Gray Level Co-occurrence Matrix (GLCM). It is a statistic method for image texture analysis. The Gray level Co-occurrence is the matrix where indices are the different gray level of the image.
- The **classification** is the last step in which the disease is detected throw the analysis of features extracted from the images. In the literature, the classification algorithms are sub-divided into two categories: binary classification and multi-class classification. Table 1 groups the main existing classification methods according to theirs types.

Table 1.Main classification methods

Classification methods	**Type of classification**
Linear regression	Binary
Support Vector Machine (SVM)	multi-class
Neural network	multi-class
Decision tree	multi-class
Genetic algorithms	multi-class

The image segmentation [2] is the most significant step because its results impact deeply on the quality of the further remaining steps.

The image segmentation [3] is an operation that consists of dividing an image into different regions in order to be analysed. There is not a single segmentation for an image. The choice of the appropriated technique depends on:

- **The nature of the image**: non-homogeneous lighting, reflection, presence of noise, textured areas, fuzzy outlines, etc.
- **The operations downstream of segmentation**: location, measurement, 3D calculation, pattern recognition, interpretation, diagnosis, quality control.
- **The operating constraints**: algorithmic complexity, operation in real time, the size of the computer memory available [4].

2.2. Image Segmentation Approaches

Image segmentation algorithms can be divided into two categories depending on the discontinuity and similarity properties. These properties lead to three main image segmentation approaches: region-based segmentation, edge-based (contours-based) segmentation and hybrid segmentation based on specific theories.

- **region-based segmentation** aims to divide the image as pixels of different regions with the same characteristics. As region-based segmentations, we may split and merge or use k-means clustering, region growing, thresholding, etc.
- **edge-based segmentation**, contrary to the region-based approach, this approach consists in determining the boundaries between the image regions. According to [5], there are three types of borders: points, lines and outlines. An outline can be defined as a sudden variation of grey level in an image with a given amplitude, a slope or a variation of the intensity of neighbouring pixels. It can also be defined as a border between two homogeneous regions [6].
- **hybrid approach** using specific theories combined both edge-based and region-based approach. It used theories like clustering, genetic algorithm, fuzzy logic and artificial neural network [7].

We may summarise the different approaches of image segmentation in Fig. 2.

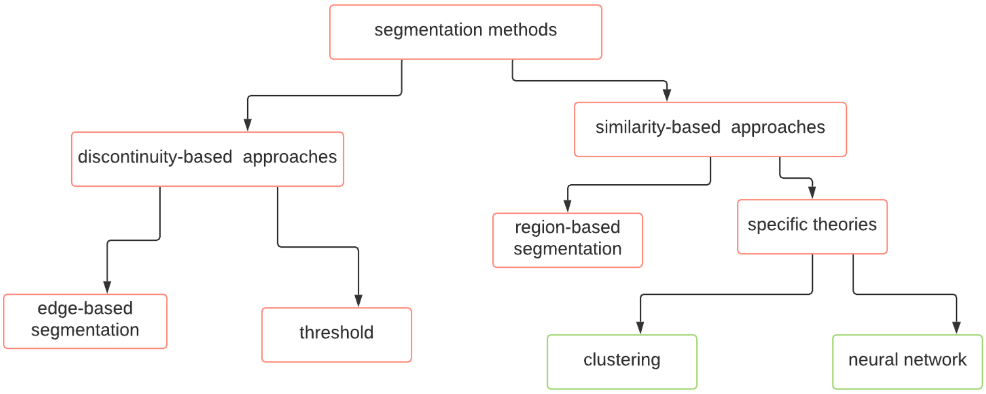


Fig. 2. Segmentation approaches

2.3. Disease Detection using Image Segmentation Techniques

Evaluating the segmentation of an image is an operation which consists of judging the quality of the segmentation of an image. Many researches have been done on the realization of segmentation algorithms but less to evaluate them. Develop good quality assessment measures segmentation algorithms is consider as difficult problem. For some researchers this is even impossible because several applications can work well using different segmentations. According to [17, 18, 19] the evaluation of segmentation algorithms can be divided into two categories: objective evaluation and subjective evaluation. The objective evaluation is divided into two categories: direct assessment and system-based evaluation. We can still divide the direct evaluation into two i.e. analytical methods and empirical methods and finally empirical evaluation in supervised evaluation and unsupervised. One method can combine several others.

Many works have been carried out dealing with the process of plant disease detection using image processing.

Elangovan and Nalini [8] propose an approach to detect diseases based on cycles. This technique of image processing aims to determine the colour and shape of a leaf affected. The process follows more or less the main steps describe in Fig. 1: acquisition of images, pre-treatment, segmentation using the k-means algorithm and then classification using the SVM algorithm.

Trini [9] proposes an algorithm that uses the thresholding and k-means algorithm for segmentation of the affected leaf image. Artificial Neural Networks (ANN) is used for the classification. This algorithmic approach has been tested on potatoes, apples and mangoes leave. This algorithm is fast and allows obtaining some good classification results.

Dhambal et al. [10] also propose an approach that considers the five steps as in [2, 3,7] to detect diseases, images are taken and resized under 256 x 256 pixels. Once reprocessing operations are performed to improve the quality, the k-means algorithm is then used to partition the image. The characteristics of the image here are extracted using the GLCM method and saved as vectors. Finally, the SVM algorithm is used to classify the plant disease. This method produces a prediction rate of 90%.

Sukhchain and Rachna [11] propose a technique for detecting fungal diseases on grapes. For this, they use the genetic algorithm for segmenting images of the grape leaf. This method produces a prediction rate of 97.1%.

Nagasai and Jhansi [12] present a disease detection approach on rose leaves. In this work, affected rose images are used and resized to size 200 x 200 pixels and saved. The canny operator is used as edge-based segmentation technique. The conversion to the HSI (hue, saturation, intensity) colour space of the image makes it possible to determine the affected portion of the leaf as well as the average and the median of the HSI pixels. These values are then stored as vectors. The Euclidean distance is used to compare the new vector to those contained in the database. Here the classification is made thanks to the SVM algorithm.

Vijai e al. [13] proceeds to the collection of a set of images in public directories. These images have been resized and filtered to eliminate noises. Then, the image segmentation is done using the Otsu and k-means algorithm. Finally, image characteristics such as contrast, correlation, energy, homogeneity, and average are retrieved to classify the disease.

Due to the amount of data to be processed, some researchers have looked at the combination of image processing and data mining to detect plant diseases [14]. Again, their approach consists of the four steps described in Fig. 1: image acquisition, image pre-processing, segmentation using the k-means and Otsu algorithm, and classification using neural networks. This work reduces clustering time and quantifies the area infected by the disease. Otsu method is a global thresholding focusing on the gray value of the image. An attempt of comparing Otsu methods is done in [1].

Meena et al. [15] suggest an approach to detect cotton disease. In this method, segmentation is done using the Otsu segmentation algorithm. To classify the disease, the following properties have been extracted from the image: contrast, dissimilarity, energy, homogeneity, entropy, correlation, mean and standard deviation. An algorithm based on fuzzy logic has been used to process the classification. This method was able to produce a prediction rate of 88%.

3. Methodology of evaluating Image Segmentation Algorithms

Our methodology starts with the collection of some sample of image of plants cultivated in the region of Adamawa. To implement and evaluate the k-nearest neighbour (k-nn), k-means clustering and the canny edge segmentation algorithms, we set up an environment based on Python language associated with diverse libraries that are used to process image data.

3.1 Workflow Process

We propose to combine diverse algorithms for image segmentation (*k-nn, k-means clustering and canny edge*), feature extraction (*GLCM*) and classification (*SVM*) in a single system. Doing so, we can evaluate the main segmentation algorithms via a single system for plant disease detection. The workflow in Fig. 3 presents the different steps of the process of the algorithm evaluation.

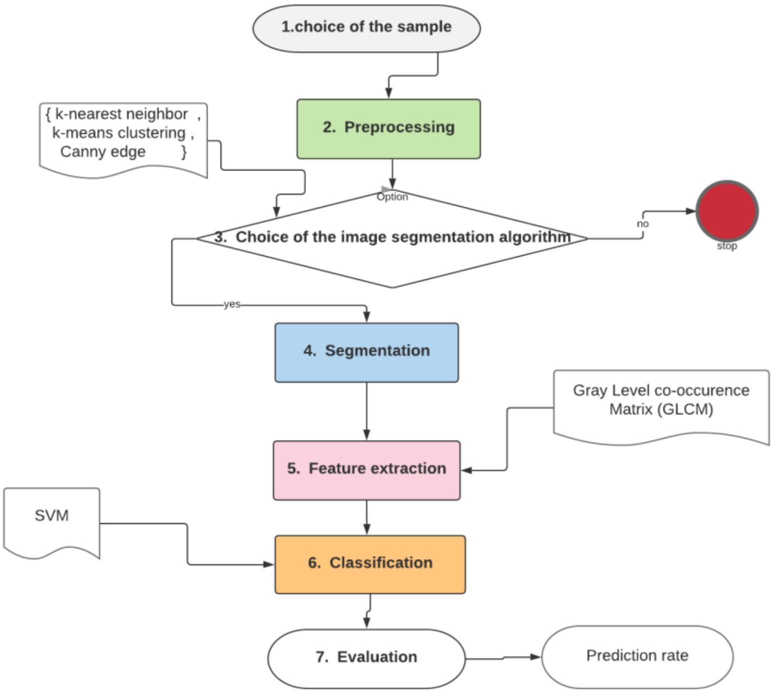


Fig. 3. Process of algorithm evaluation based on plan images

1. **Choice of the sample** starts by selecting several images of different plants. In our case study, we have used images used from the plantVillage Nuru project [16] (corn, potato and tomato).
2. **Pre-processing** improves the image quality by removing unnecessary information and noises.
3. **Choice of the image segmentation algorithm**; an algorithm is chosen from a set of algorithms (*k-nn*, *k-means clustering and canny edge*) to be evaluated and tested on the previous selected sample of images.
4. **Segmentation**; from the previous chosen algorithm, the segmentation of the image sample is carried out.
5. **Feature extraction**; this step intervenes to gather essential information from the image in order to facilitate the classification process. For this purpose, the GLCM method is used. The extracted features are: *energy*, *entropy*, *contrast*, *homogeneity* and *correlation*.
6. **Classification**; the classification is done using SVM.
7. **Evaluation**; this step is done using the *Receiver Operating Characteristic Curve* (*ROC*) and *Area Under Curve* (ROC-AUC) curve. The ROC-AUC curve is a curve which plots the true positives rate based on the false positive rate. The AUC value is used for evaluation corresponding to the prediction rate.

3.2 Dataset

To evaluate our algorithms, we choose three samples of images extracted from the images used for the implementation of the FAO plantVillage Nuru application [16] . The PlantVillage dataset consists of 54,303 healthy and unhealthy leaf images divided into 38 categories by species and disease. Our first sample is made up of corn leaves, the second of potato leaves and the third of the tomato leaves.

Description of the sample of corn leaf images: it is constituted of 40 images: 10 images of healthy plants, 10 images of plants affected common rust, 10 images of leaves affected by cercospora leaf spot which is a fungal disease, 10 images affected by blight.

Description of the sample of potato leaf images: this sample consists of 48 images divided as follows: 16 images of healthy leaves, 16 images of leaves attacked by blight at an early stage, 16 images of leaves affected by blight at an advanced stage.

Description of the sample of tomato leaf images: it consists essentially of 10 images of healthy tomato leaves, 10 images tomato leaves affected by early blight, 10 images of tomato leaves affected by blight at an advanced stage and 10 images of tomato leaves affected by the spot bacteria.

Table 2. Samples of test images [16]

	healthy	**cercospora**	**Common rust**	**blight**	**blight at an early stage**	**blight at an advanced stage**
Corn	10	10	10	10	-	-
Potato	16	-	-	-	16	16
Tomato	10	-	-	-	10	10

4. Implemented Approach and Results obtained

In order to build the segmentation tool for the evaluation for plant disease detection, we set up a development environment relying on some programming language, open source tools, specification and code of the needed algorithms.

4.1 The Development Environment

The tools and libraries needed for the implemented are listed and described in Table 3.

Table 3. Needed tools in the development environment

Tools	**Description and Utility**
Python	Python is an interpreted, high-level, general-purpose programming language.
OpenCV	OpenCV is a library of programming functions mainly aimed at real-time computer vision. In our case we used OpenCV-Python under the open-source BSD license.
Scikit-learn	It is a Python library for machine learning. It is used for classification, regression, or clustering algorithms such as decision tree forests, k-averages, etc.
Wingware	An Integrated Development Environment (IDE) supporting the Python language.

4.2 Justification and Specification of the chosen Algorithm

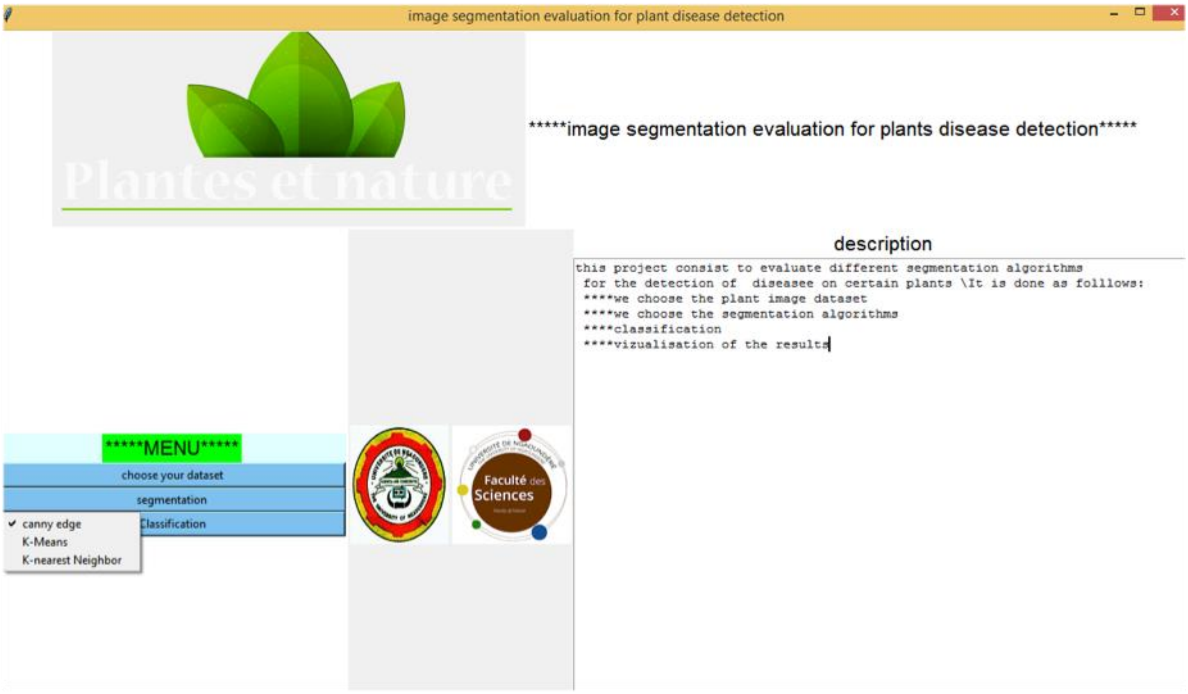
We choose to evaluate the k-nn, k-means clustering and the canny edge segmentation algorithm because there are amount the most used segmentation algorithms.

The SVM algorithm is a supervised learning algorithm. It performs the classification by determining a hyperplane to differentiate at best several classes. A short algorithm specification using the python programming language is as follows.

```
#Import Library
from sk learn import svm
#Assumed you have, X (predictor) and Y (target) for training data set and
x_test(predictor) of test_dataset
# Create SVM classification object
model = svm.svc (kernel='linear', c=1, gamma=1)
# there is various option associated with, like changing kernel, gamma and C value.
# Train the model using the training sets and check score
model.fit (X, y)
model.score(X, y)
#Predict Output
predicted= model.predict(x_test)
```

4.3 Description of the developed Tools

Accordingly, the developed tool (Fig. 4) presents a menu containing three main actions: the choice of the dataset, the segmentation and the classification activity. Therefore, we upload images of corn, tomato or potato into the system using the function “choose your dataset”. Afterwards, we proceed with the segmentation and classification.



```
this project consist to evaluate different segmentation algorithms
 for the detection of  diseasee on certain plants \It is done as folllows:
 ****we choose the plant image dataset
 ****we choose the segmentation algorithms
 ****classification
 ****vizualisation of the results
```

Fig. 4. Tool for segmentation and classification of plant diseases

4.4 Results according to Plant and Segmentation Algorithm

Before processing with the classification, we proceed with the image segmentation activity. Fig. 5, 6 and 7 represents the results of the segmentation process for corn leave using respectively canny edge, k-means clustering and k-nn.

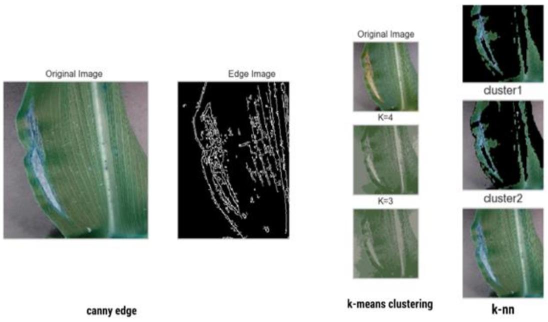


Fig. 5. Segmentation results using three algorithms on corn

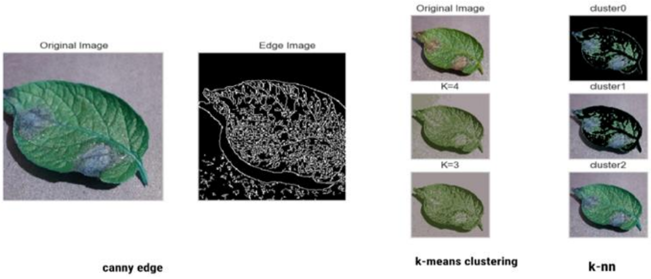


Fig. 6. Segmentation results using three algorithms on potato

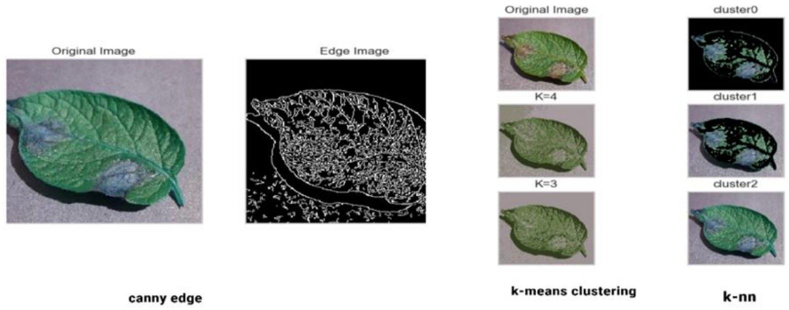
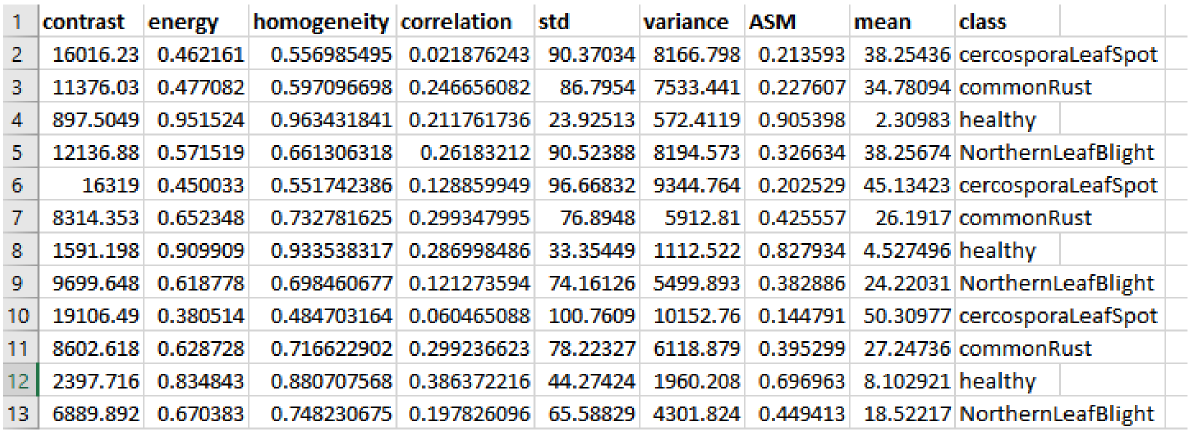


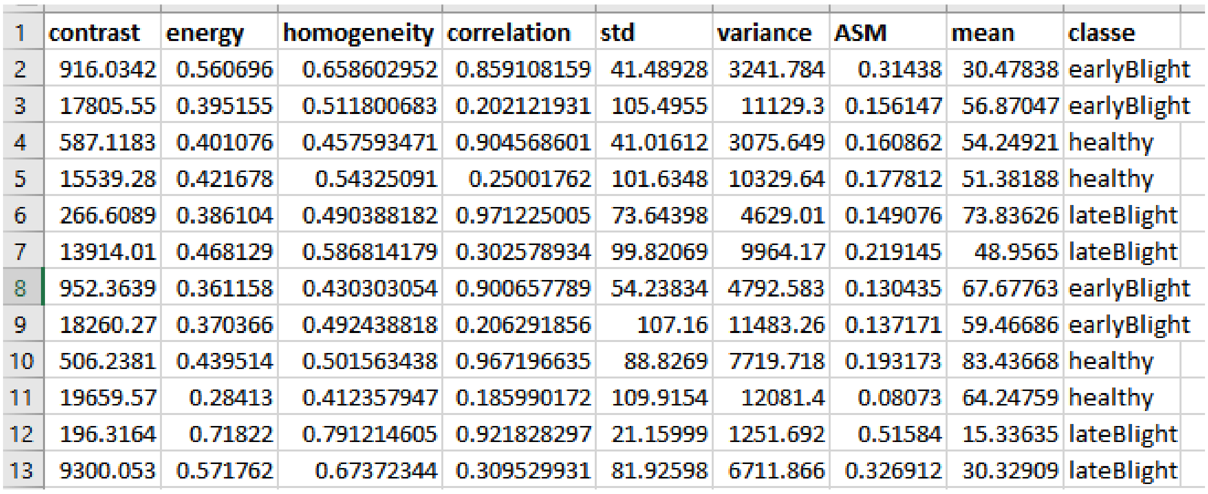
Fig. 7.Segmentation results using three algorithms on tomato

Other results of this phase are the generated data used for the classification. Some examples of the data are shown in Fig. 8 and Fig. 9 using the k-mean segmentation algorithm. Accordingly, data are generated for canny edge and k-nn algorithms.



1	contrast	energy	homogeneity	correlation	std	variance	ASM	mean	class
2	16016.23	0.462161	0.556985495	0.021876243	90.37034	8166.798	0.213593	38.25436	cercosporaLeafSpot
3	11376.03	0.477082	0.597096698	0.246656082	86.7954	7533.441	0.227607	34.78094	commonRust
4	897.5049	0.951524	0.963431841	0.211761736	23.92513	572.4119	0.905398	2.30983	healthy
5	12136.88	0.571519	0.661306318	0.26183212	90.52388	8194.573	0.326634	38.25674	NorthernLeafBlight
6	16319	0.450033	0.551742386	0.128859949	96.66832	9344.764	0.202529	45.13423	cercosporaLeafSpot
7	8314.353	0.652348	0.732781625	0.299347995	76.8948	5912.81	0.425557	26.1917	commonRust
8	1591.198	0.909909	0.933538317	0.286998486	33.35449	1112.522	0.827934	4.527496	healthy
9	9699.648	0.618778	0.698460677	0.121273594	74.16126	5499.893	0.382886	24.22031	NorthernLeafBlight
10	19106.49	0.380514	0.484703164	0.060465088	100.7609	10152.76	0.144791	50.30977	cercosporaLeafSpot
11	8602.618	0.628728	0.716622902	0.299236623	78.22327	6118.879	0.395299	27.24736	commonRust
12	2397.716	0.834843	0.880707568	0.386372216	44.27424	1960.208	0.696963	8.102921	healthy
13	6889.892	0.670383	0.748230675	0.197826096	65.58829	4301.824	0.449413	18.52217	NorthernLeafBlight

Fig. 8. Data structure for corn using k-mean segmentation algorithm



1	contrast	energy	homogeneity	correlation	std	variance	ASM	mean	classe
2	916.0342	0.560696	0.658602952	0.859108159	41.48928	3241.784	0.31438	30.47838	earlyBlight
3	17805.55	0.395155	0.511800683	0.202121931	105.4955	11129.3	0.156147	56.87047	earlyBlight
4	587.1183	0.401076	0.457593471	0.904568601	41.01612	3075.649	0.160862	54.24921	healthy
5	15539.28	0.421678	0.54325091	0.25001762	101.6348	10329.64	0.177812	51.38188	healthy
6	266.6089	0.386104	0.490388182	0.971225005	73.64398	4629.01	0.149076	73.83626	lateBlight
7	13914.01	0.468129	0.586814179	0.302578934	99.82069	9964.17	0.219145	48.9565	lateBlight
8	952.3639	0.361158	0.430303054	0.900657789	54.23834	4792.583	0.130435	67.67763	earlyBlight
9	18260.27	0.370366	0.492438818	0.206291856	107.16	11483.26	0.137171	59.46686	earlyBlight
10	506.2381	0.439514	0.501563438	0.967196635	88.8269	7719.718	0.193173	83.43668	healthy
11	19659.57	0.28413	0.412357947	0.185990172	109.9154	12081.4	0.08073	64.24759	healthy
12	196.3164	0.71822	0.791214605	0.921828297	21.15999	1251.692	0.51584	15.33635	lateBlight
13	9300.053	0.571762	0.67372344	0.309529931	81.92598	6711.866	0.326912	30.32909	lateBlight

Fig. 9. Data structure for potato using k-mean segmentation algorithm

4.5 Classification Results according to Plant and Algorithm

Considering the generated data as shown in Fig. 10 and Fig. 11, we use ROC AUC as evaluation metrics. A ROC curve is a graph showing the performance of a classification model at all classification thresholds. The tool produces diverse curves of support vector classification (SCV). For our classification, we divided each dataset as follows: 80% for training and 20% for the test purpose.

4.5.1 Results for Corn

Fig. 10 shows the results of the classification using canny edge on corn. Here we have a higher value of the AUC: micro-average ROC curve with AUC=0.92 and macro-average ROC curve with AUC=0.94 which correspond to a very good classification.

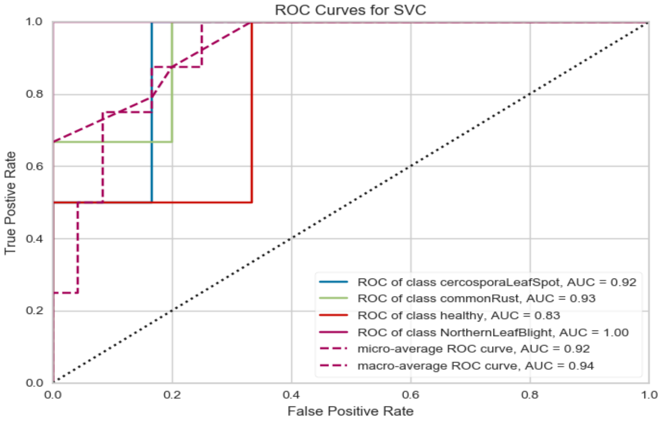


Fig. 10. Results of classification using canny edge on corn

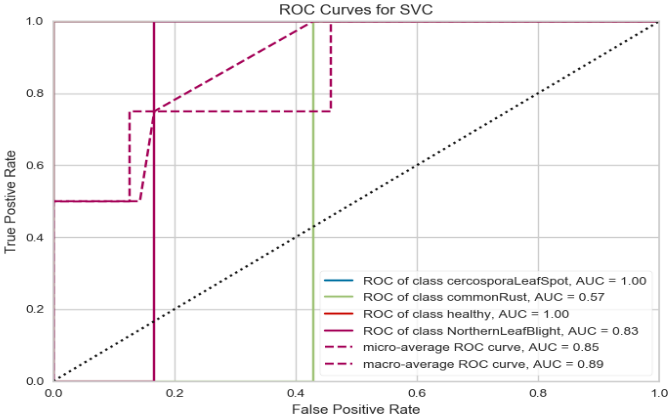


Fig. 11. Results of classification using k-means on corn

Fig. 11 shows the result of classification using k-means on corn. Here we have some good values of the AUC: micro-average ROC curve with AUC=0.85 and macro-average ROC curve with AUC=0.89 which correspond to a good classification.

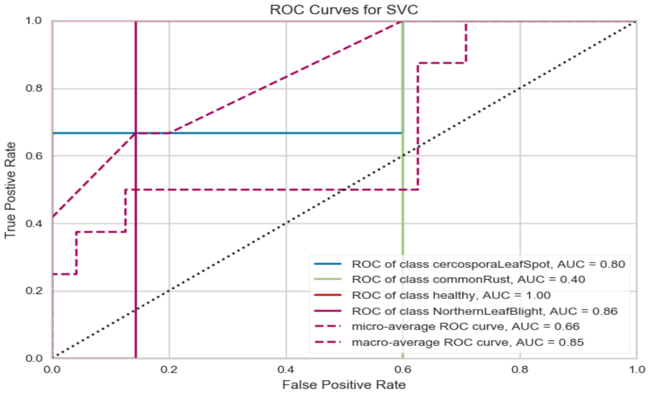


Fig. 12. Results of classification using k-nn on corn

Fig. 12 shows the result of classification using k-nn on corn. Here we have some acceptable values of the AUC: micro-average ROC curve with AUC=0.66 and macro-average ROC curve with AUC=0.85 which show acceptable classification result. This result is due to the difficulty to choose an appropriate cluster before classification.

4.5.2 Results for Potato

Fig. 13 shows the result of classification using canny edge on potato. Here we have some low values of the AUC: micro-average ROC curve with AUC=0.60 and macro-average ROC curve with AUC=0.86 which correspond to a low classification result. This result can be justified by a fact that potato presents clear borders on theirs leaves.

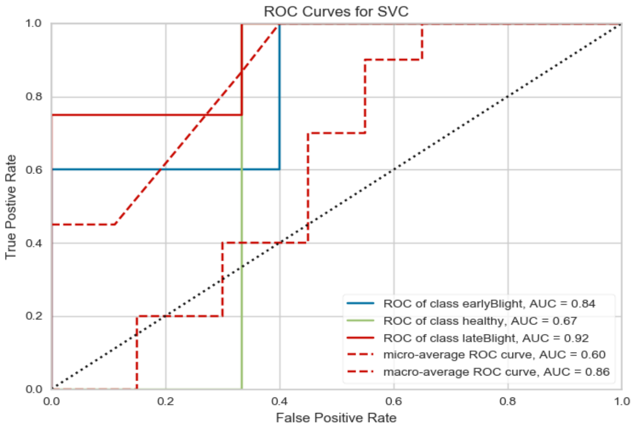


Fig. 13. Results of classification using canny edge on potato

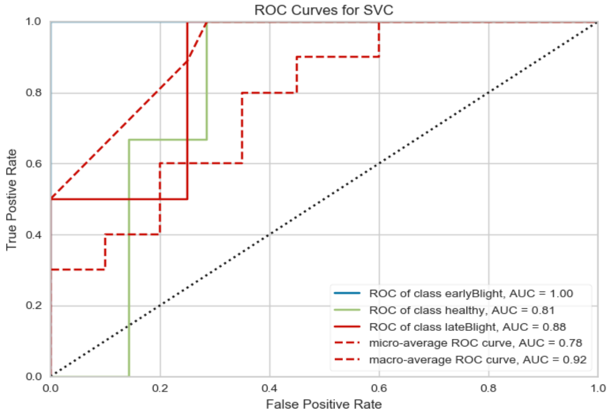


Fig. 14. Results of classification using k-means on potato

Fig. 14 shows the result of classification using k-means on potato. Here we have some good values of the AUC: micro-average ROC curve with AUC=0.78 and macro-average ROC curve with AUC=0.92 which correspond to a good classification.

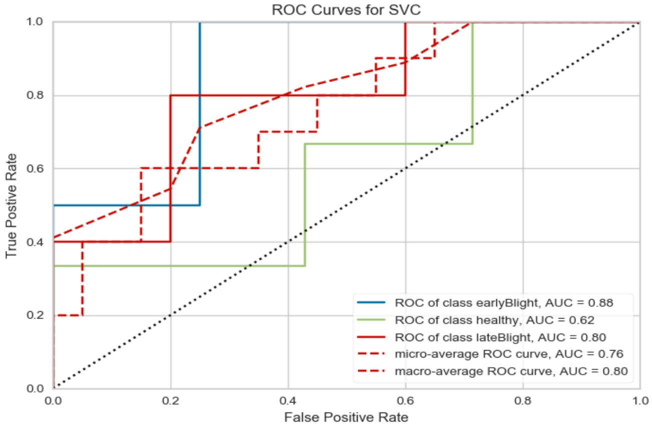


Fig. 15. Results of classification using k-nn on potato

Fig. 15 shows the result of classification using k-nn on potato. Here we have values characterised as low of the AUC: micro-average ROC curve with AUC=0.76 and macro-average ROC curve, with AUC=0.80 which correspond a low classification result.

4.5.3 Results for Tomato

Fig. 16 shows the result of classification using canny edge on tomato. Here we have values characterised as low of the AUC: micro-average ROC curve with AUC=0.78 and macro-average ROC curve with AUC=0.80 which correspond to a low classification result. This result can be justified by a fact that potato presents clear borders on theirs leaves.

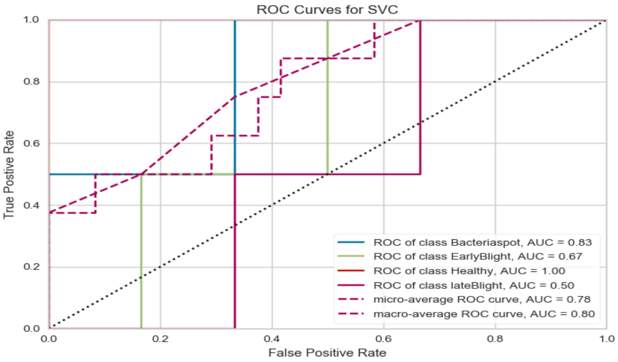


Fig. 16. Results of classification using canny edge on tomato

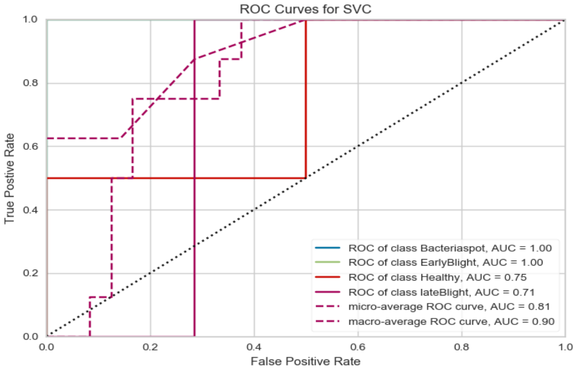


Fig. 17. Results of classification using k-means on tomato

Fig. 17 shows the result of classification using k-means clustering on tomato. Here we have a good value of the AUC: micro-average ROC curve with AUC=0.81 and macro-average ROC curve with AUC=0.90 which correspond to a good classification result.

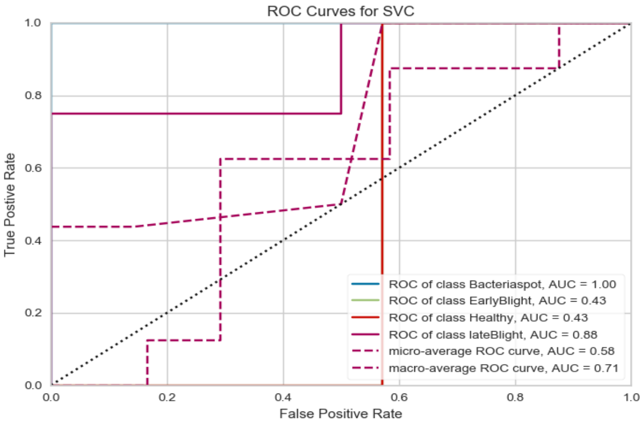


Fig. 18. Results of classification using k-nn on tomato

Fig. 18 shows the result of classification using k-nn tomato. Here we have a very low value of the AUC: micro-average ROC curve with AUC=0.58 and macro-average ROC curve with AUC=0.71 which correspond to a very bad classification result. This result is justified by the difficulty to choose the cluster that will be used for classification.

4.6 Lessons learnt from the Results

According to the results obtained on the ROC curves as well as the values of the micro-average and macro-average of AUC, we observe that:

- The canny edge algorithm performs well for the detection of corn diseases (0.94%) compared to potato (0.86) and tomato diseases (0.80%).
- For the detection of diseases on potato and tomato, the k-means algorithm is more appropriate than the other two.
- In general, the k-nn algorithm produces poor performance due to the difficulty of choosing the cluster to be used for the detection and the k value.

We also note that the canny edge algorithm allows a good prediction of corn diseases compared to those of solanaceae plant family.

5. Conclusion and Outlook

In this work, we have evaluated some segmentation algorithms for the detection of plant diseases in the region of Adamawa. First, we start by reviewing literature related to the image processing and disease detection using some existing segmentation techniques. We focused on understanding the phases and the importance of image analysis and image segmentation in the field of plant disease detection. After realising the insufficiency of works done towards the comparison of popular image segmentation algorithms, we decided to suggest an evaluation approach of those algorithms. Therefore, a tool has been built considering some dataset of plant images. The prediction results of the disease are done through the AUC values of the ROC curves obtained after the classification of the disease using the SVM algorithm. It emerges from this work that certain segmentation algorithms perform better in detecting diseases of some plants compared to others. This is the case of the canny edge algorithm that produces good classification of corn sample but it has a poor performance on samples of potatoes and tomatoes that belong to the solanaceae family. For the detection of diseases of potato and tomato plant, the k-means algorithm is the more appropriate one compared to the canny edge and k-nn algorithm. We conclude that depending on both the plant image and the disease as well, it is important to go through diverse image segmentation algorithms or techniques in order to obtain the best results by conducting a comparison. Our tools provide here a first approach combining k-nearest neighbour (k-nn), k-means clustering and the canny edge segmentation algorithms in a single platform.

As future works, we plan to extend our model to perform the evaluation of combined segmentation algorithms and also to extend the dataset of plant disease in order to cover a large amount of plants. Detecting early plant diseases will contribute to improve the harvest and also to combat desertification in general.

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