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Abstract

Plant disease severity is the ratio between the surface area of disease symptoms and the total surface area of the plant unit (e.g. fruit, leaf). It is related to plant disease diagnosis and has several advantages for farmers. It is therefore a key element in the protection and management of plant diseases. In the literature, there are three proposed categories of plant disease severity determination solutions: those based on segmentation algorithms, those based on classical ML algorithms and those based on DL algorgorithms. Despite their many advantages, these solutions have a number of limitations, including i) subjectivity in data labeling, ii) loss of information on disease lesion contours during (manual) data labeling, and iii) the proposed solutions have focused on estimating plant disease severity from leaves, although diseases can also affect other parts of the plant, such as fruits. In this paper, we present a solution for estimating the severity of four mango fruit diseases, namely alternaria, anthracnose, aspergillus rot and stem rot. This solution is based on ResNet50 CNN and uses a dataset automatically labeled by a proposed algorithm based on two segmentation algorithms such as image color space segmentation and image thresholding. The solution has achieved a accuracy and a F1_score of 97.82% and 97.79%, respectively, on test data. It is then deployed in a mobile application with a diagnostic solution we previously proposed. This mobile application will help mango growers, particularly those in Sahelian countries like Senegal, to manage their mango diseases earlier.

Keywords: Image Thresholding, Color space segmentation, CNN, ResNet50, Mango Diseases, Severity

1 Introduction

Diagnosing a plant disease and determining its severity are two related and complementary tasks. Diagnosis identifies the disease, while determining its severity gives an idea of how advanced it is. The severity of a plant disease we're interested in here is the ratio between the surface area of disease symptoms and the total surface area of the plant unit (e.g. fruit, leaf) [1]. The knowledge of a plant disease severity has many advantages for farmers including i) disease control rationalization, ii) predicting epidemics in their fields and yield losses, iii) a better pesticide management, iv) disease forecasting, v) spatio-temporal epidemic modeling and crop loss modeling [2]. It is therefore a key element in the protection and management of plant diseases. Several solutions for assessing the severity of plant diseases have been proposed in the litterature. In our paper [2], we carried out a study of 47 articles proposing solutions for the automatic assessment of plant diseases severity. Such solutions can be divided into three categories : the first category concerns solutions based on image segmentation algorithms, the second corresponds to solutions based on classical ML algorithms and the last concerns those based on DL algorithms. Disease severity assessment can be *qualitative* (see figure 1) or *quantitative* (see figure 2). It is qualitative when it comes to defining levels of severity based on visual notation, generally carried out by an expert (phytophatologist). For example, Wang et al.[3] performed a qualitative estimation of apple black rot disease using Early, Middle and End severity levels, using DL algorithmes. Abdulridha et al.[4] also propose a qualitative severity assessment of downy mildew on watermelon leaves using *Low, medium 1, medium 2, high and very high* severity levels. The severity assessment is quantitative when it involves a direct calculation of the percentage of disease lesions on the plant unit (e.g. leaf, fruit, etc.). This is the case of Escargo et al.[5] who performed a quantitative severity estimation by defining percentage intervals and assigning each interval a severity level. For example, healthy (< 0.1)%, very low (0.1%-5%), low (5.1%-10%), high (10.1%-15%) and very high (> 15)%. Bhujel et al.[6] proposed a solution that directly calculates the percentage of lesions caused by gray mold on strawberry leaves.

These solutions have achieved excellent performances, but have a number of limitations, including i) subjectivity in the labeling of data in the second category, ii) losses of information on disease lesion contours during (manual) labeling of data in the third category, and iii) the solutions proposed focused on estimating plant disease severity from leaves, although diseases can also affect other parts of the plant, such as the fruits [2]. The two first limitations have a direct impact on the quality of the data used, which in turn has a negative impact on the overall performance of the proposed solutions.

In this paper, we present a solution based on DL, particularly, ResNet50 Convolutional Neural Network (CNN) for qualitative estimation of the severity of four mango fruit diseases such as *Alternariose, Anthracnose, Aspergillus rot and Stem and rot.*

This solution uses a dataset automatically labeled by a proposed disease severity calculation algorithm based on two image segmentation algorithms, namely *image color space segmentation* and *image thresholding*.
The specific contributions of this paper include:

- To determine the severity of mango diseases, not from leaves, but from infected fruits.
- To eliminate human intervention in data labeling, i.e. the division of data into different severity levels (classes) in the case of a qualitative disease severity assessment.

The rest of the document is organized as follows: Section 2 deals with the dataset and algorithms used in this work, Sections 3 presents and discusses the results obtained, The final Section concludes the paper and announces the authors' future work.

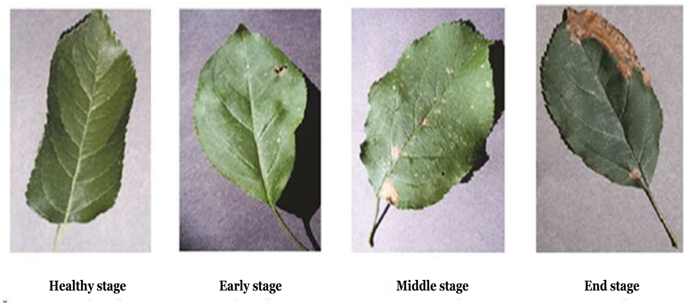

Fig. 1 Example of qualitative estimation of apple rot severity [3]

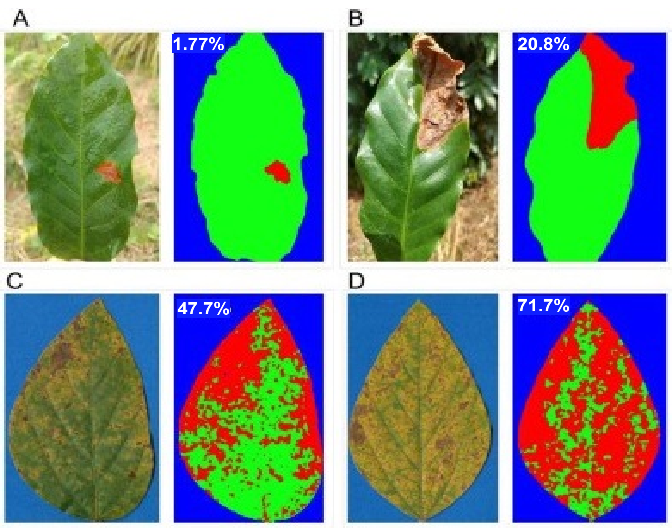

Fig. 2 Example of quantifying the severity of leaf diseases based on lesion segmentation [7]

2 Material and Method

2.1 Datataset used

In this work, we have used our dataset *SenMangoFruitDDS* presented in our paper [8]. It is downloadable from Mendeley data plateform via the url https://data.mendeley.com/datasets/jvszp9cbpw/3. This dataset contains 862 mango fruit images of four diseases such as Anthracnose, Alternariose, aspergillus rot and Stem and rot. The infected fruits in the images show different stages of severity. The dataset also contains, as additionnal category, images of healthy mango fruits. Mango fruit images are gathered from an orchard located in Senegal, using mobile phone camera. Images collected in the field are pre-processed using techniques such as cropping, resizing and background removal to improve their quality. Images are in JPG format and have a uniform size of 224*224. Figure 3 gives an overview of the composition of SenMangoFruitDDS.

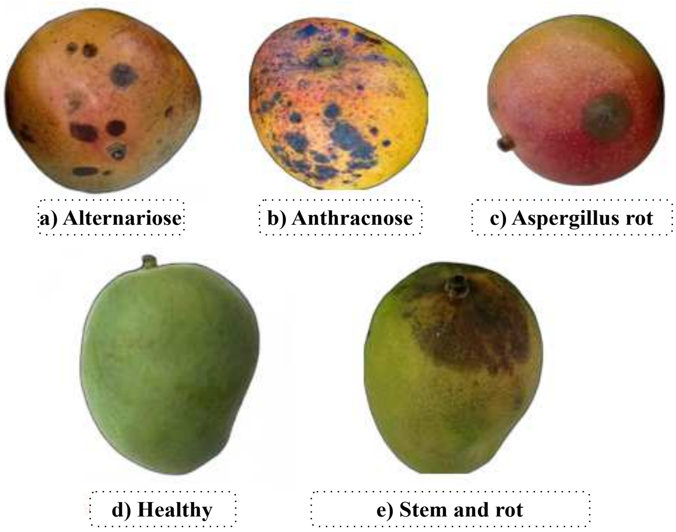

Fig. 3 Composition of the dataset: it contains five classes containing different numbers of images: 170 images for Alternariose class, 132 images for Anthracnose class, 186 images for Aspergillus rot class, 166 images for Stem and rot class and 208 images for Healthy class.

2.2 Segmentation algorithms

Severity quantification involves calculating the percentage of infected areas (disease symptoms) on a mango fruit images. In this work, we used two image segmentation algorithms namely *image color space segmentation* and *image thresholding*. Image segmentation is a computer vision task that automatically divides an image into pixel areas belonging to the same object class. It is an important task in image processing, facilitating the characterization, delineation and visualization of regions of interest in an image. Image segmentation is widely used in the medical field, particularly in medical imaging [9].

2.2.1 Image color space segmentation

One of the most important aspects of vision is color. It is generally used to recognize or discriminate information. From a physical point of view, color is caused by the reflection of part of the light in an object [10]. Digital images have color channels that are represented by color spaces. It's these color spaces that give an image its distinctive color. There are several color spaces, the most widely used are RGB (Red, Green, Blue), HSV (Hue, Saturation, Value), CMYK (Cyan, Magenta, Yellow, Black), etc. RGB is the default color space for digital images. Each color channel (red, green and blue) has a value between 0 and 255. If all channels are set to their maximum value, the image color is white. If they are all set to 0, the image color is black. A digital image can be converted from one color space to another. Image segmentation can be based on the color space [11, 12]. We used this algorithm with the RGB color space to segment images by converting them into binary images, i.e. images in which the the mango fruit is represented in black and the background in white. In this way, the surface area (S_{fruit}) of the mango fruit in an image corresponds to the total number of pixels in black.

2.2.2 Image Thresholding

Image thresholding algorithm converts a colored image into a binary image, with one part indicating the foreground and the other corresponding to the background. The idea behind thresholding is to make a colored image very easy to analyze by dividing its pixels into two classes [13]. In computer vision, the colored image is first converted into a grayscale image, i.e. an image in which all colors are shades of gray. Then, each pixel in the grayscale image is compared with a threshold value. In our case, we chose 120 as the threshold value, as the pixel interval [120-255] corresponds best to our images and therefore gives the best image segmentation results after several experimental tests in the interval [0-255]. If the pixel value is below the threshold value (120), it is set to 0, otherwise it is set to a maximum value (255) (see equation 1). This value corresponds to the pixel's intensity or brightness and in a grayscale image, a pixel value of 0 represents black, and 255 represents white. If all pixels in an image are black or white, the image is binary. We used thresholding algorithm to calculate the surface area of lesions (S_{lesion}) on infected mango fruits.

$$f(x,y) = \begin{cases} 0, & \text{if } f(x,y) < T \\ 255, & \text{otherwise} \end{cases} \tag{1}$$

f(x, y) = pixel value with coordinates (x,y)
T = threshold value

2.3 Proposed severity calculation algorithm

As a reminder, calculating the severity of a disease involves determining the ratio between the surface area of lesions caused by the disease and the total surface area of the fruit (equation 2).

$$Severity = \frac{S_{\text{lesion}}}{S_{\text{fruit}}} * 100 \tag{2}$$

S_{lesion}: total number of pixels of lesions on the fruit.
S_{fruit}: total number of pixels of the fruit, including pixels of lesions.

To calculate the severity of a disease on an image, the following algorithm was applied:

1. Apply color space segmentation to input image: *it generates a binary image on which all black pixels correspond to the whole fruit and the white pixels correspond to the background.*
2. Determinate the total number of pixels corresponding to the whole fruit (S_{fruit}).
3. Determinate the total number of pixels corresponding to the background ($S_{\text{background}}$).
4. Convert input image to grayscale.
5. Apply thresholding to the grayscale image: *with a threshold value of 120, the grayscale image is converted to binary so that the total number of white pixels (SF_{white}) represent the healthy parts of the fruit and the black pixels represent the disease lesions and background.*
6. Determinate the number of pixels corresponding to the healthy parts of the fruit, i.e, the total of white pixels (SF_{white}).
7. Calculate the number of pixels corresponding to the disease lesions (S_{lesion}): $S_{\text{lesion}} = S_{\text{fruit}} - SF_{\text{white}}$
8. Calculate the percentage of the disease lesions on the fruit using the equation 2: This percentage corresponds to the disease severity.

The figure 4 represents also the steps of this proposed algorithm.The Open Computer Vision (OpenCV) library [14] is used to implement this algorithm.

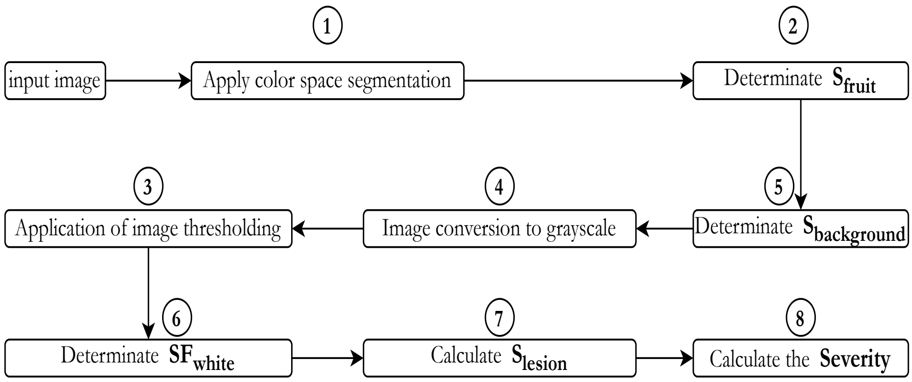

Fig. 4 Disease severity calculation workflow

2.4 Severity dataset creation

The subjectivity of data labeling is the main limitation of DL-based plant disease severity estimation solutions [2]. So the aim of this section is to present a method to create automatically a severity dataset applying the *severity calculation algorithm* to *SenMangoFruitDDS* (the dataset presented earlier). As a reminder, SenMangoFruitDDS is composed of 5 classes, namely Alternaria (170 images), Anthracnose (132 images), Aspergillus rot (186 images), Stem and rot (166 images) and Healthy (208 images). The images of the first 4 classes (classes of infected fruit) are all grouped together in a single file and subjected to the *severity calculation algorithm* proposed above. The plant pathologists we worked with to create SenMangoFruitDDS helped us define the 3 severity classes (or intervals) on the basis of which the images of infected mangoes are classified. Theses classes are following:

- **Healthy**: this class contains healthy mango fruit images. It contains the same images as the healthy class of SenMangoFruitDDS.
- **Early**: this class contains images of infected mangoes whose severity is between 0.1 and 3%. It contains images showing the first symptoms of the disease.
- **Intermediate**: disease severity is between 3 and 12%. Images in this class show advanced symptoms of the disease.
- **Final**: disease severity is greater than or equal to 12%. Images show very/extremely advanced disease symptoms.

The figure 5 illustrates the process of creating the new dataset.

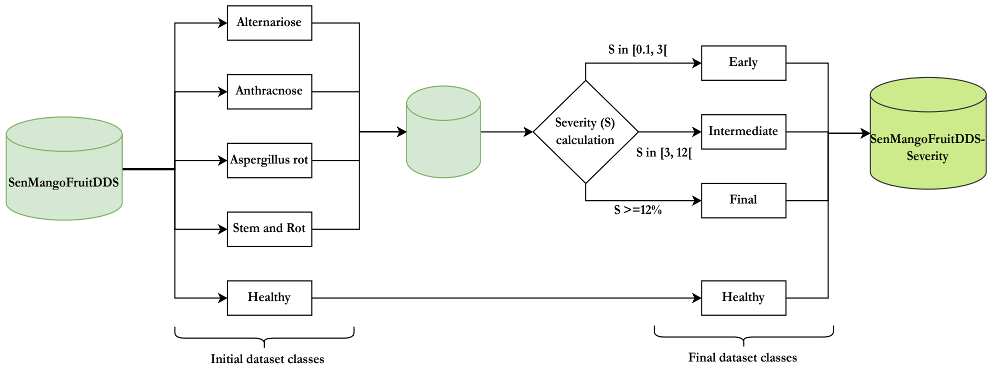

Fig. 5 Workflow of SenMangoFruitDDS-Severity dataset creation. Images of infected mangoes are automatically classified into 3 classes (Early, Intermediate and Final). Images of healthy mangoes from SenMangoFruitDDS are transferred directly to the new dataset.

2.5 CNN Model used

In our paper [8], we proposed a solution for mango disease classification using the SenMangoFruitDDS dataset. After augmenting this dataset, we trained 8 CNNs, including

7 well-known CNNs (EfficientNetBV2, InceptionV3, DenseNet121, MobileNetV2, NASNetMobile, VGG16 and ResNet50) and a lightweight CNN we proposed. According to the experimental results, ResNet50 achieved the best performance (accuracy: 98.20% and F1_score: 98.20%). In addition, the disease classification task and severity estimation we want to realise in this work are identical and use the same data (images). So, given that SenMangoFruitDDS-Severity is a small dataset (862 images), instead of augmenting it and training ResNet50 from scratch, we used the *Transfer Learning (TL)* technique. TL is a learning technique that enables a CNN to learn new and similar tasks using previously acquired knowledge [15, 16]. In other words, the knowledge acquired in a given task is reused as the starting point of a CNN for a similar task. Thus, the knowledge previously acquired by ResNet50 in our work [8] will be the starting point for training this model on SenMangoFruitDDS-Severity.
We have modified this model by replacing the number of nodes (**5**) in the softmax output layer by **4** (corresponding to the number of classes in SenMangoFruitDDS-Severity dataset). We implemented it using the Keras library. The model training parameters used include the Adam optimizer with a learning rate of 0.001, a categorical cross-entropy loss function, a batch size of 32 and a number of epochs of 10. We have frozen all the layers except the last two blocks of the pre-trained ResNet50 model, so as not to lose the previously acquired knowledge. Figure 6 shows the modified architecture of the model. The model is trained on a server equipped with an NVIDIA GPU and 32 GB or RAM.

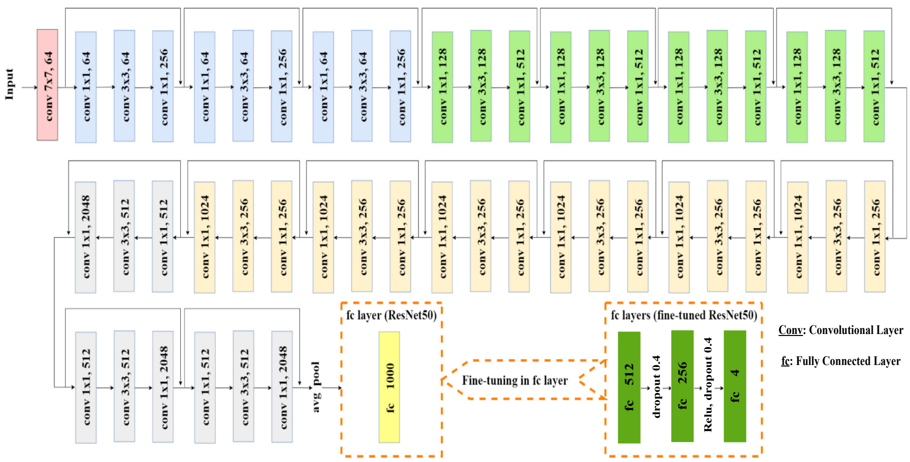

Fig. 6 Modified ResNet50 architecture (inspired by [17])

3 Results and discussions

The application of color space segmentation algorithm on RGB images of infected mangoes converted them into binary images, i.e. images in which all background pixels are in **white** and pixels of the fruit in **black** (figure 9). The background pixels have its color value RGB=(255,255,255) and intensity 255, while the fruit pixels have their color value RGB=(0,0,0) and intensity 0. The area occupied by the fruit (S_{fruit}) in the image is then the total number of pixels in black.

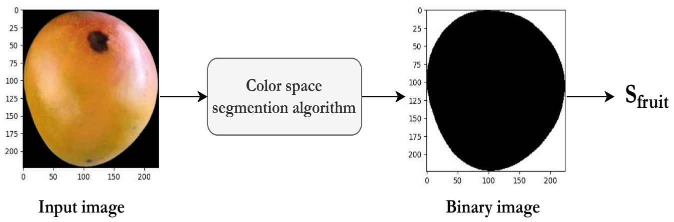

Fig. 7 Fruit surface (S_{fruit}) determination

To determine the lesion surface (S_{lesion}) on the fruit images, each image is first converted in grayscale and then subjected to the image thresholding algorithm to convert it to binary, i.e, the background and disease symptoms in black and the rest of the fruit in white, as shown in figure 8.

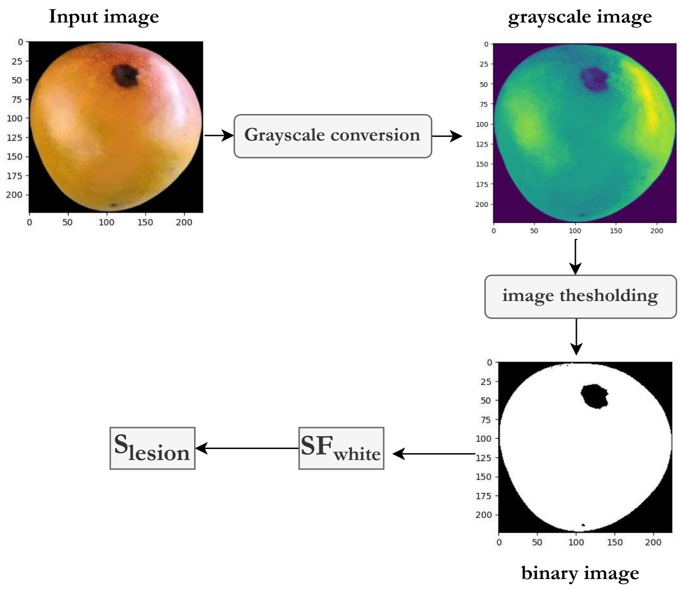

Fig. 8 Disease lesion surface determination

We call the white surface (or healthy surface) of the fruit $\mathbf{SF_{white}}$. The lesion surface (S_{lesion}) on the fruit is then obtained by the equation.

$$S_{\text{lesion}} = S_{\text{fruit}} - SF_{\text{white}} \tag{3}$$

Now that we know the values of S_{lesion} and S_{Fruit}, the severity of a disease, based on an image of an infected mango, can be quickly calculated by applying the equation 2. For example, for the first original fruit image in the figure 9, the severity of the

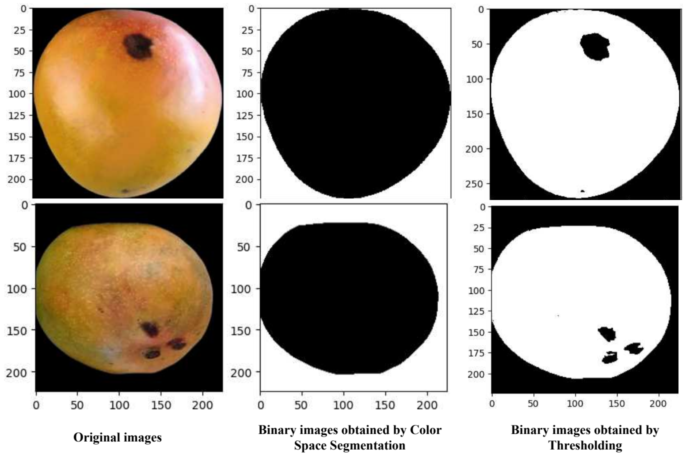

Fig. 9 Examples of image segmentation results based on color space segmentation and thresholding

disease is determined as follows:
S_{fruit} = 38745 pixel
SF_{white} = 36943 pixel
S_{lesion} = 1802 pixel
Severity = 1802/38745*100 = 4.65%
This severity calculation algorithm is then applied to all mango fruit disease images to first calculate their severity and then automatically classify them as proposed at the figure 5. We thus obtained a new severity dataset, with images automatically labeled and divided into four classes as shown in Table (1). Figure 10 shows sample images for each class in the severity dataset. The dataset is not balanced because the classes have different numbers of images. This is normal, given that image classification is performed by an algorithm.

Table 1 Composition of SenMangoFruitDDS-Severity dataset

	Classes			
	Healthy	**Early**	**Intermediate**	**Final**
Number of images	208	150	242	262
Total	862			

SenMangoFruitDDS-Severity dataset is divided into three parts: 64% (552 images) for training data, 16% (138 images) for validation data, and 20% (172 images) for

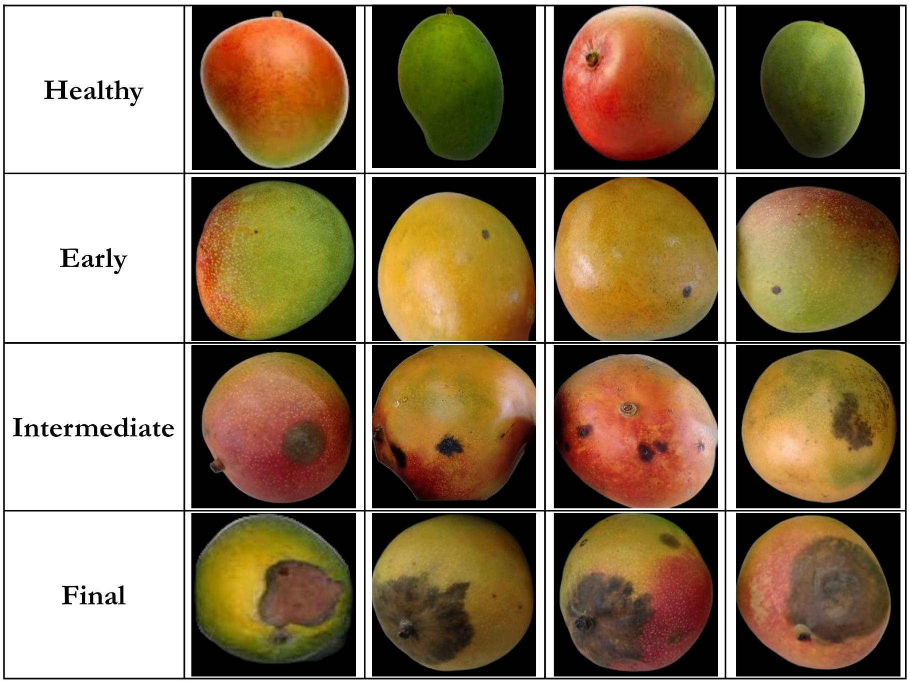

Fig. 10 Examples of images contained in each class of SenMangoFruitDDS-Severity dataset

test data. The use of the TL technique enabled the ResNet50 model, pre-trained on the MangupFruitDDS augmented dataset [8], to achieved very good classification performance on MangupFruitDDS-Severity, i.e. an accuracy of 97.82% and a f1_score of 97.79%, for estimating mango disease severity from infected fruits (figure 11). These results show i) the advantage of using TL technique for small datasets, ii) the effectiveness of the proposed solution, iii) that plant disease severity can be estimated from infected fruits rather than infected leaves, as proposed by the majority of plant disease severity estimation solutions proposed in the literature, and iv) that human intervention can be considerably reduced or eliminated when labeling data for estimating the severity of plant diseases. Today, thanks to technological advances, and in particular

	ResNet50
Training accuracy (%)	98.56
Validation accuracy (%)	98.44
Test accuracy (%)	97.82
F1_score (%)	97.79

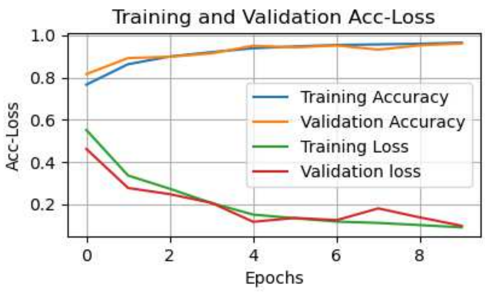

Fig. 11 Training results of ResNet50 on SenMangoFruitDDS-Severity

the improved computing capabilities of mobile devices, DL models can be deployed in smartphones via mobile applications to enable, for example, real-time diagnosis and estimation of the severity of plant diseases.
Thus, the ResNet50 model trained on SenMangoFruitDDS in our paper [8] for the classification of the four diseases concerned and the ResNet50 model trained on SenMangoFruitDDS-Severity with the TL technique are both deployed in a mobile application that we have developed using the Android programming language. The main function of this mobile application is to enable mango growers to diagnose diseases in their mango trees from images of infected fruits, without the intervention of an expert (plant pathologist), automatically, simply and in real time. After diagnosing a disease, the application also gives the user the disease severity severity level, depending on whether it is in an *early stage*, an *intermediate stage* or a *final stage*. Images can be captured directly by a smartphone or stored in its gallery (figure 12). The application works without Internet, enabling users in remote areas or without Internet coverage to use it. -

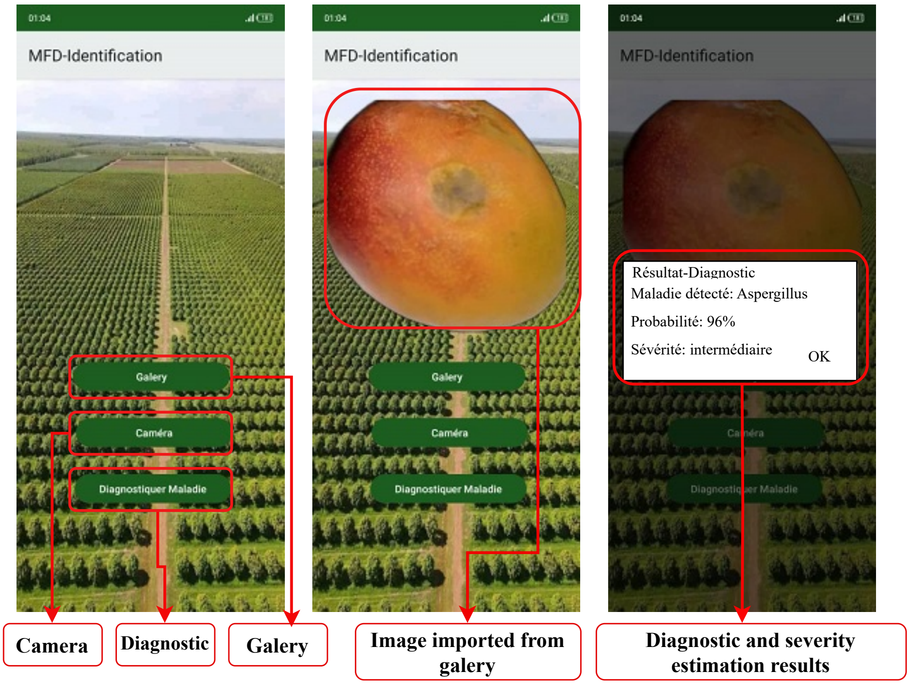

Fig. 12 Mobile application screenshots

4 Conclusion and future work

In this article, we presented a qualitative mango diseases severity estimation. Four mango fruit diseases namely alternaria, anthracnose, aspergillus rot and stem rot are considered in this work. The objectives of this work were to show that the severity of a plant disease can indeed be estimated from infected fruit, and that the data (images) can be labeled without human intervention. These objectives were achieved, since the experimental results obtained show that the ResNet50 CNN model trained on our generated severity dataset obtained an accuracy of 97.82% and an F1_score of 97.79% on test images. This solution is deployed in a mobile application with a diagnostic solution to help mango growers, particularly those in Sahelian countries like Senegal, to manage their mango diseases earlier and more effectively. In the future, we hope to extend these solutions to other plant diseases cultivated in Senegal, such as rice, onions, potatoes, etc.

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