Survey on Crop Disease Detection and Identification Based on Deep Learning

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Abstract. Plant diseases lead to a reduction in both quality and quantity of agricultural production. 50% of agricultural losses are due to these diseases. Due to poverty and lack of infrastructures in some countries, their identification remains difficult. Plant pathologists use several techniques to identify these diseases. But these techniques are time-consuming and relatively expensive for farmers. Nowadays, several models based on image processing (IP) techniques, machine learning (ML) algorithms and deep learning (DL) algorithms have been proposed for automatic detection and identification of plant diseases. In this study, we divided these models into two groups: models based on IP and classical ML algorithms, and those based on DL. DL coupled with the transfer learning (TL) technique has become the most widely used method because of its impressive performance. The critical analysis of these models has allowed us to identify potential challenges in the field of automatic plant disease diagnosis.

Keywords: Crop diseases · Automatic detection · Artificial intelligence · Image processing · Machine learning · Deep learning · Transfer learning

1 Introduction

Plant diseases have long been one of the problems leading to a considerable reduction in both quality and quantity of agricultural production [1]. Such diseases are closely related to the long-standing global climate change [2, 3] or caused by pathogens like bacteria, virus, fungi, parasites, etc. [4]. 50% of yield losses are due to these diseases or pests [5]. Its therefore constitute a major threat to global food security and also have disastrous consequences for the economy of small farmers who represent 85% of the world's farmers [6, 7].

Rapid identification of crop diseases remains difficult in many parts of the world (e.g. developing countries) due to the lack of necessary infrastructures [6] and poverty. In practice, a naked eye observation of experts is the main approach adopted for diagnosing such diseases [8, 9]. The techniques used by Plant pathologists include methods related to chemical analysis of the infected area of the plant, and indirect methods such as the use of physical techniques (spectroscopy). These techniques are relatively expensive for farmers [1] and often take a long time to find out exactly what the disease is and to propose the right remedy to treat the pathology.

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However, the search for a fast, automatic, cheaper and accurate method to detect plant diseases before its spread in the field is of great importance [1, 10]. It will prevent agricultural yields losses while at the same time ensuring crop quality and quantity. Today, precision technology based on IP, ML and DL is driving the modern agricultural revolution known as "Agriculture 4.0" which aims to revolutionize agricultural productivity and farm profitability [11]. Currently, AI technology, which crowns ML, which in turn crowns DL, is already considered a reality in the context of precision agriculture [1]. In recent years, several ML models have been proposed for the automatic diagnosis of plant diseases from their leaves, which are usually the first area where the symptoms of most plant diseases appear [12, 13]. These models offer a possibility to easily deploy this technology on mobile devices. In addition, with the important internet penetration[1] all around the world, smartphones and drones offer new tools for real-time detection of plant diseases [7].

This study consists of a critical analysis of recently proposed models based on IP, ML and DL techniques for the automatic diagnosis of plant diseases. It concludes by identifying the limitations and potential challenges that could help researchers in this field.

The paper is organized as follows: Sect. 2 shows the automatic learning algorithms used to identify plant diseases, Sects. 3 and 4 provide a critical analysis of the proposed models based on the classical ML and DL algorithms respectively, Sect. 5 defines and gives the advantages of TL, Sect. 6 shows the potential challenges in the field of automatic plant disease diagnosis and the last section concludes the paper.

2 Algorithms Used for Plant Disease Diagnosis

Several AI-based algorithms are used today to diagnose crop leaf diseases. The most commonly used are K-Nearest Neighbors (K-NN), Logistic Regression, Decision Tree, Random Forest (RF), Support Vector Machines (SVM) and Artificial Neural Networks (ANN) [9, 14, 15]. Such algorithms are combined with different IP methods for better feature extraction. In recent years, ANNs, especially Convolutional Neural Networks (CNNs), are the most widely used in the field of plant leaf disease identification [1, 3, 7, 16, 17]. From an architectural point of view, there are mainly two categories of ANNS: feed-forward ANNs, in which the output of one layer is output from any layer and is not likely to influence that same layer, and feedback ANNs, in which signals flow in both directions, involving loops in the network [18].

3 Detection and Identification of Plant Diseases Based on Classical ML Algorithms

In the field of plant disease detection and classification, classical ML algorithms, combined with IP techniques, have achieved excellent results. Image segmentation and classification are key steps in many proposed systems for plant disease detection. The objective of segmentation is to divide an image into a set of disjoint regions with uniform and

[1] The portion of the population that has access to the Internet.

homogeneous attributes such as intensity, color, tone, or texture [19]. Image segmentation approaches can be divided into four categories: thresholding, clustering, edge detection and region extraction [5]. The K-means clustering algorithm and the SVM are the most widely used algorithms in the last decade for image segmentation and classification, respectively [13, 19–21].

For example, Al Bashish et al. [10] used a model based on K-Means and a neural network to detect and classify five plant diseases namely, early scorch, cottony mold, ashen mold, late scorch and tiny whiteness, from their RGB images. K-Means technique provided excellent results in the segmentation of RGB images. The proposed model achieved an accuracy of 93%. [8] is an improvement of [10] by completely removing pixels with zero red, green and blue values and pixels at the boundaries of the infected group (object) from the images. The accuracies obtained range from 83 to 94% and the processing time has been reduced by 20% compared to the approach proposed in [10]. To detect and classify two tomato diseases caused respectively by tomato spotted wilt virus and tomato yellow leaf curl virus, Mokhtar et al. [13] proposed an approach based on four main phases, namely pre-processing, segmentation (k-means clustering algorithm) of the image, feature extraction and classification (SVM). They obtained an overall accuracy of 90% in the classification of images of diseased tomato leaves but system performance can be improved by increasing the number of images used (200 images). Chouhan et al. [19] introduced a method called Bacterial foraging optimization based Radial Basis Function Neural Network (BRBFNN) for the automatic identification and classification of plant leaf diseases using Genetic Algorithm (GA) and K-Means Clustering algorithms and SVM classifier. The accuracies obtained vary between 75.1 and 88.97%. BRBFNN is used to speed up a network and improve classification accuracy. Tian et al. [21] combined a GA to the SVM classifier and performed feature selection based on kernel principal component analysis (KPCA) to identify the best features in the images. The proposed KPCA/GA-SVM recognition model achieved the following results: 98.14%, 94.05% and 97.96% accuracy for apple mosaic virus, apple rust and apple leaf spot, respectively. Kaur et al. [22] proposed a system for detecting, classifying and calculating the severity of three soybean diseases (downy mildew, frog eye, and septoria leaf blight). Authors used color features, texture features and their combinations separately to train three models based on k-means clustering and SVM. The accuracy is ranged from 80.5 to 85%. However, the texture features selected in this study identify frog eye very efficiently but do not work for septoria leaf blight and downy mildew. Camargo et al. [23] use an algorithm for identifying visible symptoms of plant diseases based on color image analysis. The algorithm consists of the following four main phases: pre-processing, enhancement, segmentation and post-processing of images to remove unwanted background regions. To test the accuracy of their algorithm, manually segmented images were compared to automatically segmented ones. The results showed that the developed algorithm was able to identify diseased regions of plant leaves even when that region was represented by a wide range of intensities. Sutrodhor et al. [24] proposed a Mango Leaf Ailment Detection (MLAD) system based on Neural Network and SVM classifier. The MLAD can automatically detect and classify four diseases named Scab, Anthracnose, Red Rust and Sooty Mold with a mean accuracy of 80%. However, the main problem encountered is that there is not enough data on mango diseases.

Studies have shown that ML and IP algorithms have been used to determine disease severity on plant fruits. For example, Kuo et al. [25] presents an application of neural networks and IP techniques to detect and classify the quality of areca nuts, using the Detection Line method for image segmentation and a back-propagation neural network for classification. The proposed algorithm can detect spots and classify the quality of areca nuts with a CCD camera accurately (90.9%) and efficiently, but is unable to inspect for the covered blades (or other face). Table 1 is a summary of classical ML-based approaches. It compares these approaches based on the training and test data used, the ML algorithms used and the results obtained.

Table 1. Comparison of methods based on classical ML algorithms.

Topic	Year	Crop	Diseases	Method	Accuracy
[19]	2018	Orange, apple, tomato, apple	Common rust, cedar apple rust, late blight, leaf curl, leaf spot, and early blight	BRBFNN, GA et K-Means + SVM	75.17 – 88.97%
[22]	2018	Soybean	Downy mildew, frog eye, and Septoria leaf blight	k-means + SVM	80.5 – 85%
[24]	2018	Mango	Scab, Anthracnose, Red Rust and Sooty Mold	Neural Network + SVM	80%
[21]	2012	Apple	Mosaic virus, rust and alternaria leaf spot	KPCA/GA + SVM	98.14%, 4.05% and 97.96%
[25]	2012	Areca nuts	Quality of areca	Detection Line + Back-propagation neural network	90.90%
[8]	2011	Undefined	Early scorch, Cottony mold, Ashen mold, late scorch and tiny whiteness	k-Means + Neural Network	83 – 94%
[10]	2011	Undefined	Early scorch, Cottony mold, Ashen mold, late scorch and tiny whiteness	k-Means + Neural Network	93%
[23]	2009	Banana	Black sigatoka	Histogram of intensity + proposed classifier	93.7%

4 Detection and Identification Based on DL

Today, several DL models (or architectures) are used to identify plant diseases: Finetuned CNN architecture [2], Faster R-CNN [3], Region-based Fully Convolutional Network (R-FCN) [3], GoogleNet CNN [6], Inception V3 based on GoogleNet [7], Shallow CNN Model [9], Nine-layer deep CNN [14], AlexNet CNN [26], AlexNetOWTBn [16], Single-shot multibox (SSD) [28], INC VGGN [29], Deep Residual Neural Network (DRNN) [30], etc. Since AlexNet's success in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) competition in 2012, increasingly deeper networks [26, 31, 32] have been proposed and have achieved state-of-the-art performance on ImageNet and other benchmark datasets [3].

The latest generation of CNNs has achieved impressive results in image classification and is considered as the leading method for object detection in computer vision. [3, 18, 33]. For example, Ait Elkadi K. et al. [1] built a CNN-based ML model to identify tomato diseases from RGB (Red, Green, Blue) leaves images. The images used were taken from PlantVillage, a public dataset. They compared their model with three CNNs architectures, namely Alexnet, LeNet, Tairu (which provided the best performance). With the Tairu architecture, they were able to predict 8 tomato diseases with 94.35% accuracy. According to the authors, CNNs require special attention, especially in the availability of training data, the adequate choice of network structures and their hyper parameters to be adopted, and the material means available to carry out the training in the best conditions. Fuentes et al. [3] proposed a DL-based approach to detect and recognize nine different types of diseases and pests on plants in real time, using images taken by cameras (smartphones and other digital cameras). The authors used three DL architectures (Faster R-CNN (83% of accuracy), R-FCN (85.98%) and SSD (82.53%)) to find out which one is the most suitable for real-time detection and recognition of plant diseases and pests. The proposed system is able to recognize diseases but also to localize them on plant leaves and shows remarkable performance on the cases evaluated. However, the system is crop specific and, due to the insufficient number of samples, some classes with high pattern variation tend to be confounded with others, resulting in lower average precision. Mohanty et al. [6] used CNNs based on GoogleNet and AlexNet architectures to identify 14 species and 26 different plant diseases with an accuracy of 99.35%. However, for model training, when images taken under different conditions than PlantVillage are used, the accuracy drops to 31.4%. The performance of the model decreases when images taken in real time are used for testing and more training data would be sufficient to increase the accuracy of the model. Ramcharan et al. [7] applied Transfer Learning (TL) to a deep CNN (Inception V3 CNN) to identify three diseases (brown leaf spot (BLS), cassava brown streak disease (CBSD) and cassava mosaic disease (CMD)) and two types of pest damage (red mite damage (RMD) and green mite damage (GMD)). They analyzed the performance of the model with three different architectures: the original inception softmax layer, SVM, and k-nearest neighbor (knn). The model obtained the following accuracies: 98% for BLS and CBSD, 96% for CMD and RMD and 95% for GMD. The overall accuracy is 93%. Their study showed that TL applied to the CNN Inception V3 model offers very promising results in real-time plant disease detection with a relatively small image dataset. Using images or videos taken in real time by the mobile app as training data would increase the overall accuracy of the system. To identify plant diseases from their leaves, Ferentinos et al. [16] developed five CNNs based on the following architectures: AlexNet, AlexNetOWTBn, GoogLeNet, Overfeat and VGG. They used both images from a public dataset and images taken in real field conditions (37.3%) to train and test the models. When the models were trained and tested with images taken under laboratory conditions, the best performing models, VGG and AlexNetOWTBn, achieved 99.53% and 99.49% of accuracy, respectively. On the other hand, when trained and tested with images taken under laboratory conditions and those taken in the field, the accuracies decrease to 33.27% and 32.23% respectively for VGG and AlexNetOWTBn. Sladojevic et al. [18] propose a deep CNN to identify 13 different types of plant diseases with the ability to distinguish leaves of diseased plants from healthy leaves and their environment, with an average accuracy of 96.3%. However, the dataset used by the authors consists of images from Internet, so they are not taken in real conditions. Subetha et al. [27] compared the performance of two DL algorithms, such as ResNet50 and VGG19, in classifying and predicting the apple leaf diseases using images from Kaggle dataset and others real-time images captured in an apple orchard under different environmental conditions such as illumination, varying backgrounds, view-invariant, and various noises. The results show VGG19 can work better in real-time compared to ResNet50 but these architectures can predict the leaf disease with an overall accuracy of 87.7%. Pham et al. [34] proposed a Feed-Forward Neural Network (FFNN) with Hybrid Metaheuristic Feature Selection (HMFS) to classifier 3 mango diseases named Anthracnose, Gall Midge, and Powdery Mildew. The proposed model achieved an accuracy of 89,41% more than comparative CNN named AlexNet (78.64%), VGG1 (79.92%) and ResNet (84.88%). Singh et al. [35] used a multilayer convolutional neural network (MCNN) model for the classification of the mango leaves infected with the fungal disease named as anthracnose. They pre-trained their images using histogram of equalization (for contrast enhancement) and central square crop method (for image resizing) and achieved an accuracy of 97.13%. But images taken in real condition majorly suffers from the problem of Variation in Temperature, Shadowing, Overlapping of leaves, and Presence of multiple objects. Such problems reduce the performance of the model. Gulavnai et al. [36] proposed a ResNet-CNN (ResNet18, ResNet34 and ResNet50) combined with TL for automatic detection and identification of four mango leaf diseases named, anthracnose, powdery mildew, red rust and golmich. Results show that ResNet50 gives better performance with an accuracy of 91.50%. Piyush Singh et al. [37] developed a Deep 2D-Convolutional Neural Network (CNN) to detect stem bleeding disease, leaf blight disease, and pest infection by Red palm weevil in coconut trees by applying IP and DL technology. They used TL technique and compared their model to VGG16, VGG19, InceptionV3, DenseNet201, MobileNet, Xception, InceptionResNetV2 and ASNetMobile. InceptionResNetV2 and MobileNet obtained a classification accuracy of 81.48% and 82.10%, respectively while the hand-designed CNN model achieved 96.94% validation accuracy. Rabia Saleem et al. [38] proposed a model based CNN and named FrCNnet to segment and identify the diseases (Anthracnose and apical nacrosis) on the mango leaves using TL. The proposed model's segmentation accuracy is 99.2%. But a large number of mango images are required to improve the segmentation performance of each class.

Over the years, researchers have continued to develop deeper and more powerful CNN models. Geetharamani et al. [14] developped a deep CNN model with nine layers to solve plant leaf disease identification problems using PlantVillage dataset. To achieve better performance and accuracy (96.46%), they had to improve the model training images using the following methods: image flipping, gamma correction, noise injection, color enhancement by principal component analysis (PCA), rotation and scaling. The authors believe that extending their database with new images of different plant species and from different sources would increase the performance and accuracy of their model.

However, studies have shown that it is not necessary to use deep CNNs just to identify plant diseases. Shallow CNNs have a powerful IP capability which, when combined with classical ML algorithms (e.g. KNN, SVM, Random Forest (RF),…) can provide excellent results exceeding those of the proposed deep CNNs [9]. Shallow CNNs use few parameters, which means that its require little learning time.

Today, researchers are increasingly applying transfer learning (TL) [7, 14, 28, 29, 32] (see Sect. 4) to train their models for better performance. Chen et al. [29] investigated TL of deep CNNs to identify plant leaf diseases with minute lesion symptoms with the objective of reducing computational complexity. The proposed model achieves 91.83% accuracy on the PlantVillage dataset and 92% accuracy for class prediction of rice diseased images collected under real field conditions with fairly complex backgrounds.

Thanks to the benefits of TL (see Sect. 4), these models are increasingly being integrated into applications for use in mobile devices such as smartphones, drones and other autonomous agricultural vehicles. For example, Ramcharan et al. [28] deployed a CNN model in a mobile application to identify leaf symptoms (pronounced and mild) of three diseases (Manihot, esculenta, Crantz), two types of damage (RMD and GMD) caused by pests and the lack of nutrients in cassava. The authors used the SSD model and the MobileNet detector and classifier and tested the system with images and videos taken in real time and real field conditions. They obtained an accuracy of 80.6% for images and 70.4% for videos for named symptoms. But for mild symptoms, they obtained 4.10% for images and 29.4% for videos. The detection of mild symptoms seems to be difficult. One solution would be to use images with mild symptoms as training data.

Studies have shown that using a balanced set of images as the dataset increases the classification accuracy for a given model. For example, Oyewola et al. [30] developed a deep residual neural network (DRNN) and a Plain Convolutional Neural Network (PCNN) for the recognition of cassava leaf diseases. They used the distinct block processing technique and a balanced dataset of cassava leaf images, which was biased towards the CMD and CBSD classes. The proposed DRNN model outperformed PCNN by a significant margin of 9.25% on the Kaggle cassava disease dataset. Therefore, using the imbalanced dataset of cassava leaf images, both PCNN and DRNN fail identify well cassava diseases (PCNN: 50–65%; DRNN: 50% of accuracy).

Information on disease severity is crucial for plant pathologists when proposing remedies (e.g. pesticides) to eradicate a disease. This will allow pesticides to be used more economically while preserving the environment. For example, Ozguven et al. [39] used a faster R-CNN model to automatically detect and estimate disease severity in sugar beet leaves. The model was trained and tested with 155 images and the overall correct classification rate was found to be 95.48%. The authors believe that using more data and improving the quality of the images will also increase the performance of the model. Gensheng Hu et al. [17] developed a DL method based on Faster R-CNN architecture to both detect and estimate the severity of tea leaf blight (TLB). They used Retinex algorithm to enhance quality of original images used. The proposed method reduces the impact of the imbalance in the number of images and improves the accuracy of gravity classification by increasing the image size and separating the detection and classification tasks. Results show that the detection average precision and the severity grading accuracy of the method are improved by more than 6% and 9%, respectively, compared with the classical ML methods.

Table 2 is a summary of the DL-based approaches in terms of the architecture used, the training and test data used and the accuracy of the proposed model.

Table 2. Comparison of deep learning approaches

Topic	Year	Data used	Architecture	Accuracy
[1]	2021	PlantVillage	Alexnet, LeNet, Tairu and proposed model	94%
[17]	2021	Images captured in tea garden	Faster R-CNN	i) Disease detection: 6% more than classical ML methods ii) Disease severity analysis: 9% more than classical ML methods
[24]	2021	Dataset of hand-collected images of coconut	2D-CNN, VGG16, VGG19, InceptionV3, Dense-Net201, MobileNet, Xception, InceptionResNetV2 and SNetMobile	i) 2D-CNN: 96.94% ii) Inception-ResNetV2: 81.48% iii) MobileNet: 82.10%
[27]	2021	Kaggle dataset + 3,651real-time apple images	ResNet50 and VGG19	87.7%
[30]	2021	Kaggle dataset	DRNN	96.75%
[37]	2021	Hand-collected dataset of 1564 images	Deep 2D-CNN	96.94%
[38]	2021	2286 real-time self-collected mango images	FrCNnet	99.2%
[6]	2020	PlantVillage	GoogleNet et AlexNet	99.35%
[29]	2020	PlantVillage and real time images	INC-VGGN	i) Images from PlantVillage: 91.83% ii) Real time images:92%

(*continued*)

Table 2. (*continued*)

Topic	Year	Data used	Architecture	Accuracy
[34]	2020	Dataset of 450 images of mango leaves	FFNN with HMFS	89.41%
[14]	2019	PlantVillage	Proposed	96.46%
[28]	2019	COCO dataset and digital camera images	SD-MobileNet	i) images: 80.6%; videos: 70.4% for pre-named symptoms ii)For mild symptoms, images: 4.10%; videos: 29.4%
[35]	2019	1070 mango leaves images captured on real-time and 1130 images from PlantVillage	MCNN	97.13%
[36]	2019	Mango dataset of 8853 images	ResNet-CNN	91.50%
[39]	2019	Dataset of 155 sugar beet images	Faster R-CNN	95.48%
[16]	2018	Public Dataset	AlexNet, lexNetOWTBn, GoogLeNet, Overfeat and VGG	i) VGG: 99.53%; ii) Overfeat: 99.49%
[3]	2017	Images taken by different cameras	Faster R-CNN, R-FCN and SSD	i) Faster R-CNN: 83%; ii) R-FCN: 85.98%; iii) SSD: 82.53%
[7]	2017	Images captured in a field	Inception V3 CNN	93%
[18]	2016	Images downloaded from the Internet	CaffeNet	96.30%

5 Transfer Learning

TL is a ML approach in which a trained CNN for one task is reused as a starting point for a model for a second task [40]. This knowledge sharing method reduces the training data size, time and computational costs when building a DL model [14]. With TL, instead of training a model from scratch, the model can be initialized using a pre-trained network on large labeled datasets, such as public image datasets, etc. [29] (see Fig. 1).

TL has been used in various applications, such as plant classification, software defect prediction, activity recognition and sentiment classification. In recent years, in the field of plant disease detection and identification, this technique has been widely used in DL approaches since the models often used in this field require high computational time and resources. TL has shown excellent results with deep network models. In general, there are three types of TL: from prior knowledge to learning, from learning to new learning and from learning to application [41].

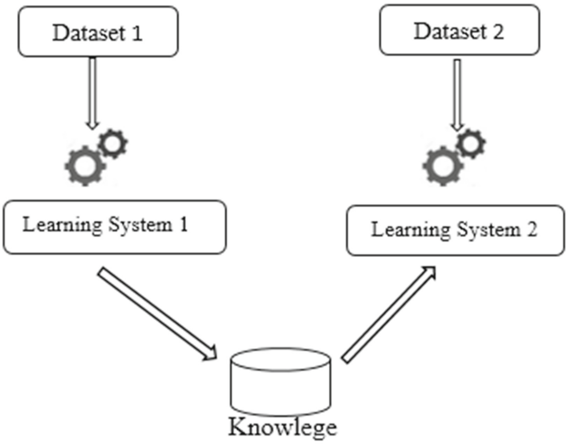

Fig. 1. Transfer learning technique

6 Potential Challenges

Classical ML algorithms and DL algorithms have achieved excellent results in the field of automatic plant disease diagnosis. However, the following challenges remain:

- For DL approaches, training data should be taken in the field and in geographically different locations (or sources). This will allow very good results to be obtained when testing with images taken in real time, in the field.
- For test images, it is important to consider images that are noisy, poorly illuminated or have complex backgrounds.
- One of the limitations of the proposed models is the difficulty of detecting diseases with mild symptoms. Detection of these mild symptoms would allow early detection of plant diseases.
- The symptoms of crop diseases can also appear on roots, stems, flowers or fruits. But until now, researchers are focused on foliar diseases.
- With the advantages of TL, these models should be deployed in mobile devices to help farmers diagnose crop diseases quickly, but also plant pathologists in their decision making. However, it should be taken into consideration that in developing countries (e.g. Sahelian countries), there is no internet in many areas, especially in the most remote areas.

7 Conclusion

This paper presents a review of approaches used for automatic detection and identification of plant diseases. These approaches are divided into two categories: classical ML based approaches and DL-based approaches. In recent years, DL-based approaches are the most widely used and for this purpose, the best performances are obtained with CNNs. In this study, we have critically analyzed these approaches to identify both limitations and potential challenges for future researches in the field of automatic crop diseases diagnosis. For future work, we plan to develop a model based on DL and the TL technique to allow farmers, especially those in Sahelian countries such as Senegal, from mobile devices (smartphone, tablet, etc.), to be able to diagnose the diseases of their crops without the intervention of experts. We will focus on mango diseases, as this fruit is one of the most produced and traded crops in Senegal. This will lead to a smarter and more sustainable production of mango in this developing country.

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