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RESEARCH ARTICLE

Segment Anything Model and Fully Convolutional Data Description for Plant Multi-Disease Detection on Field Images

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ABSTRACT Researchers have designed various models trained on public or private datasets for plant disease detection to help farmers remedy crop yield losses on their farms due to plant diseases. Plantvillage is the most widely used plant disease dataset with laboratory images captured under controlled conditions with a single leaf on each image and a uniform background. Models trained on such datasets have extremely low classification accuracies when running on field images captured directly from plantations with various interwoven leaves, complex backgrounds, and different lighting conditions. In this study, we propose a model ensemble solution for the accurate identification and classification of plant diseases using field images. The model uses Segment Anything Model to efficiently circumscribe all identifiable objects in the image. Image Processing techniques are then used to isolate the identified objects from the original image. Background objects are separated from actual leaf objects using Fully Convolutional Data Description, which is an explainable deep one-class classification model for anomaly detection. Finally, the selected leaves are submitted to a Plantvillage-trained classification model for inference. Our model can detect diseases appearing on individual leaves of the same image and improves classification accuracy by more than 10% on public field plant disease datasets such as PlantDoc, thus providing a reliable solution for farmers and practitioners.

INDEX TERMS Field plant images, fully convolutional data description, laboratory images, plant disease dataset, plant disease detection and classification, segment anything model.

I. INTRODUCTION

In Cameroon, many farmers face legal problems following yield losses due to diseases that affect their plantations. Indeed, such outbreaks give farmers little or no time to take appropriate countermeasures, it is no longer possible for them to repay the debts contracted to start their agricultural projects. Currently, plant disease detection and classification have become a major research concerns.

The lack of chlorophyll in plant leaves due to some diseases causes them to die or results in a significant decrease in their production. Manual inspection of plantations is time-consuming and impractical for bigger plantations, thereby reducing crop production. Consequently, many smart agricultural practices have been deployed to control plant diseases. Computer Vision and Machine Learning techniques

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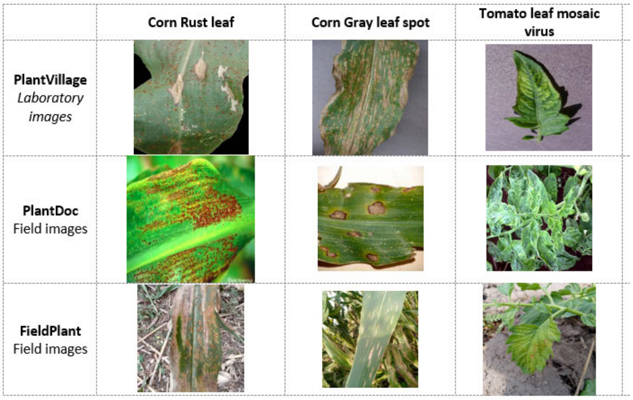

FIGURE 1. **Some plant disease images under laboratory and field conditions.**

have been extensively considered by researchers to tackle this issue by providing farmers with tools to help prevent crop losses. The early detection of plant diseases can significantly minimize the need for various chemical products for plant growth and consequently reduce the negative impact of these products on the environment.

A. RESEARCH CONTEXT

Many deep Convolutional Neural Networks (CNN) have been used to differentiate healthy leaves from diseased leaves using captured images [1]. Sujatha et al. [2] showed that Deep Learning methods perform better than classical Machine Learning methods (Support Vector Machine (SVM), Random Forest (RF) and Stochastic Gradient Descent (SGD)) in disease detection. The first systematic literature review on plant disease detection covering both localization and disease classification was conducted by Shafik et al. [3]. This is a crucial research field to avoid crop losses by taking suitable countermeasures, especially given that the Food and Agriculture Organization of the United Nations (FAO) recommends increasing food supply by 70% by 2050 [4].

The quality of the models built for plant disease detection relies mainly on the datasets used to train them. Many datasets have been suggested for this purpose, including the PlantVillage [4], iBean [5], citrus [6], rice [7], cassava [8], and AI Challenger 2018 datasets [9]. These datasets are essentially composed of laboratory images which are images of single leaves collected from plant and placed on top of a uniform background before being photographed. These images were also captured under controlled climatic and lighting conditions. Fig. 1 highlights the differences between laboratory plant disease image datasets and in-field datasets.

The performance of classification tasks on these laboratory images is usually very high; however, when these models are run on field images their performance decreases significantly. Field images contain many interwoven leaves and complex backgrounds, thereby providing considerable noise for the classification of the CNN models. As such, plant disease classification systems trained on laboratory images are not effective in practice with field images because of the structural difference between laboratory and field images [10], [11] [12]. The lack of available multi-crop in-field datasets is one of the most significant obstacles to consider when developing plant disease detection models that can perform adequately in real-time [3].

In [13], CNN models were developed to perform plant disease detection and diagnosis using simple leaf images of healthy and diseased plants, using laboratory and in-field images. At the end of the study, the authors showed how the performance of the models varies according to different training/testing scenarios with respect to laboratory conditions and field-condition images, as shown in Table 1.

TABLE 1. **Models' performance with different training/testing scenarios in respect to laboratory-conditions and field-conditions images [13].**

	Training: Laboratory - Testing: Field	**Training: Field - Testing: Laboratory**
Model	Success rate	Success rate
AlexNetOWTBn	32.23%	62.57%
VGG	33.27%	65.69%

B. PROBLEM, CONTRIBUTIONS AND ORGANIZATION

Detection of plant diseases in natural environments remains a significant research challenge. Barbedo [14] highlighted in their research that CNN are powerful tools that can suitably deal with plant disease detection and classification. The main limitation still preventing wider use of this kind of tool in practice is not technical but practical; building databases comprehensive enough for the creation of truly robust tools is very challenging. It is necessary to make further improvements in the field of plant disease localization studies to accomplish accurate disease detection at the field level. Most existing models use pre-trained CNN and their ensemble can improve performances in the identification and classification of different plant diseases [3], [15].

In this study, we propose a model ensemble solution for plant multi-disease identification and classification of field images. The model uses Segment Anything Model [16] to identify all objects present in the input field plant image. Accurate parameters were used to identify almost all objects present in the image: leaves, stems, branches and background. In the next step, all identified objects are submitted to a Fully Convolutional Data Description (FCDD) [17] model, a Deep One-Class Classification module, trained to differentiate plant leaves from any other object. Finally, only the selected ROI is retained for inference on the PlantVillage-trained classification module for the final output. Depending on the user, this ROI can be the largest identified leaf for a single prediction or all identified leaves for multi-disease predictions. The model outperforms all current classification tasks on the PlantDoc datasets.

TABLE 2. Transfer Learning doubled the accuracy after finetuning on Uncropped PlantDoc dataset [18] but we notice a very low accuracy when training on PlantVillage and testing on Plantdoc.

PreTrained Weights	Training Set(%)	Test Set(%)	Accuracy
ImageNet	PlantDoc (80)	PlantDoc (20)	13.74
ImageNet	PVD (100)	PlantDoc (100)	15.08
ImageNet+PVD	PlantDoc (80)	PlantDoc (20)	29.73

The remainder of this paper is organized as follows. Section II discusses various plant disease detection datasets and different plant disease detection models, highlighting challenges such as dataset limitations and lack of generalizability. The proposed model is presented in Section III, utilizing the Segment Anything Model (SAM) and Fully Convolutional Data Description (FCDD). Finally, Section IV highlights the model experiments, showing improvements in the validation accuracies, precision, recalls and F1-scores of state-of-the-art CNN models on various datasets, with open-source code provided for further exploration and a mobile app developed for farmers.

II. RELATED WORK

A. PLANT DISEASE DETECTION DATASETS

Although there are several datasets related to plant diseases, PlantVillage and PlantDoc remain the two most publicly available. Fig. 1 shows the three main publicly available plant disease datasets used in this study.

1) PLANTVILLAGE

PlantVillage [4] is the largest plant disease dataset containing laboratory images. It contains 54,309 images spanning 14 crop species across 38 classes of plant diseases and one class of background. With Transfer Learning, 99.9% accuracy can be easily achieved when training a deep learning model on the PlantVillage dataset to distinguish between healthy and diseased leaves. However, when the same models are used for inference in field images, with multiple interwoven leaves and complex backgrounds, their performances decrease significantly [10], [11], and [12].

2) PLANTDOC

One way to overcome this challenge is to use field images to train models. PlantDoc [18] was the first plant disease dataset of field condition images for various situations. The dataset contains 2,598 data points across 13 plant species and 17 classes of diseases. Each image is annotated with bounding boxes to identify all healthy or diseased leaves in the image. With transfer learning, it was possible to reach an accuracy of 29.73% on the plant disease classification task on the original uncropped PlantDoc dataset as presented in Table 2.

The biggest challenge in plant disease identification from field images is to construct a sufficiently accurate CNN that can first identify the plant shown in the image as well as the associated disease, which is quite a difficult task.

TABLE 3. Plant disease classification benchmark on FieldPlant dataset [19].

CNN Model	Training set(%)	Test set(%)	Acc.
MobileNet	PV(100)	PD(100)	16.75
	PD(80)	PD(20)	60.14
	PV(100)	FP(100)	**61.92**
	FP(80)	FP(20)	**82.9**
VGG16	PV(100)	PD(100)	12.75
	PD(80)	PD(20)	40.3
	PV(100)	FP(100)	**15.27**
	FP(80)	FP(20)	**80.54**
InceptionResNetV2	PV(100)	PD(100)	17.32
	PD(80)	PD(20)	48.38
	PV(100)	FP(100)	**52.87**
	FP(80)	FP(20)	**81.81**
InceptionV3	PV(100)	PD(100)	14.25
	PD(80)	PD(20)	51.27
	PV(100)	FP(100)	**43.85**
	FP(80)	FP(20)	**82.54**

3) FIELDPLANT

The main limitations of the PlantDoc dataset are i) the use of poor-quality images downloaded from the Internet, ii) the absence of plant pathology experts during the collection and annotation phases and iii) the presence of many laboratory images in the dataset. To overcome these limitations, Moupojou et al. proposed the FieldPlant dataset [19], which contains 5,170 field condition images captured directly from Cameroon plantations and annotated under the supervision of plant pathologists. In their evaluation of the dataset, the authors achieved an accuracy of 82.9% for the classification task on the FieldPlant raw image dataset.

A benchmark was run on the FieldPlant dataset to evaluate its accuracy compared to the PlantVillage and PlantDoc datasets. In the benchmark results in Table 3, PV, PD, and FP represent the PlantVillage, PlantDoc, and FieldPlant datasets, respectively.

4) PLANT DISEASE DATASET 271 (PDD271)

PDD271 [20] is a large-scale plant disease dataset comprising 271 plant disease categories and 220,592 images. The dataset includes field photographs of vegetables, grains, fruits, and tree plants. Based on this dataset, plant disease recognition

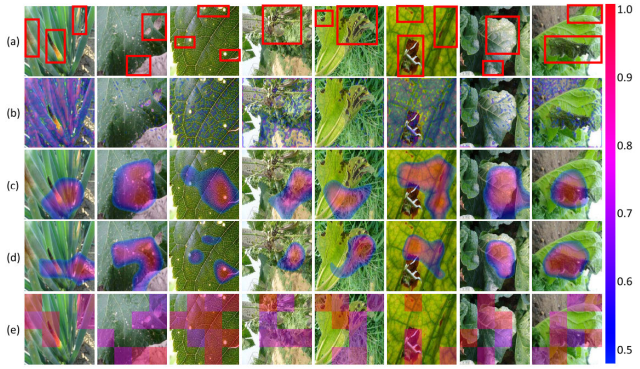

FIGURE 2. **(a) Original image with diseased parts annotated by red boxes, (b) Feature map from the last convolution layer of VGG16, (c) Feature map from the last convolution layer of ResNet152, (d) Feature map from the last convolution layer of SeNet154, (e) Visualisation of the proposed CRR weights for each patch. The red means high weights and the blue means relatively low weights [20].**

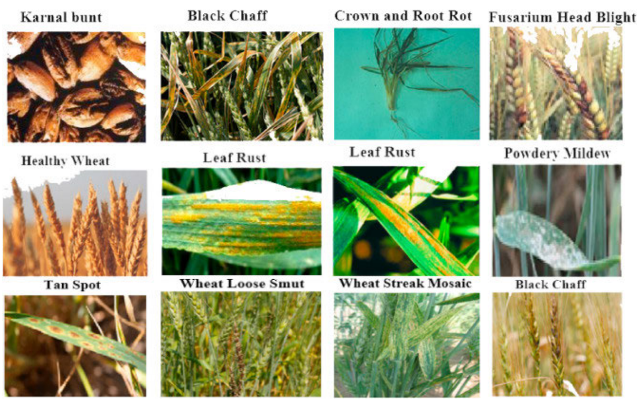

FIGURE 3. **Samples selected from the collected dataset LWDCD2020 [21].**

is tackled by reweighting both visual regions and loss to emphasize diseased parts, in order to enable discriminative disease part learning, as shown in Fig. 2. Unfortunately, this dataset is not publicly available but is owned by Beijing Puhui Sannong Technology Co. Ltd.

5) LARGE WHEAT DISEASE CLASSIFICATION DATASET (LWDCD2020)

LWDCD2020 [21] contains 12,160 images of wheat diseases organized into nine disease classes and one healthy class, collected under actual field conditions as shown in Fig. 3. The images were preprocessed for dimensional uniformity. LWDCD2020 images include complex backgrounds, various capture conditions, various characterizations of distinct stages of disease evolution, and similar features between different wheat diseases.

B. PLANT DISEASE DETECTION MODELS

Deep learning has been widely used to detect and classify plant diseases. In contrast to classical machine-learning techniques that are needed to first design the morphological operations of feature extraction, deep learning has the ability to automatically learn hierarchical pathological features. Many researchers have relied on existing CNN models such as MobileNetV2 [22] or YOLO [23] to propose solutions, whereas others have suggested original models for plant disease classification tasks. Some researchers have also used their own collected datasets to evaluate their models, making their reproducibility very difficult, while many others have relied only on public datasets such as PlantVillage or PlantDoc.

1) LABORATORY IMAGES MODELS

Many deep-learning models use laboratory images to evaluate their performances. This is useful in providing the first sense of model behaviour, which can be further improved by considering field images. These models often exhibit high accuracy.

Khattak et al. [24] proposed an attention-embedded residual CNN for disease detection in the tomato leaves. The research exploited the features learned by the CNN at various processing hierarchies using the attention mechanism and experiments conducted using the PlantVillage dataset comprising three different diseases achieved an accuracy of 98% on the validation sets in the 5-fold cross-validation.

One of the challenges in plant disease detection is the distribution of disease symptoms on the leaves. Xiao et al. [25] suggested a new lightweight model based on an advanced residual network and attention mechanism called SE-VRNet to extract more accurate regions of interest and lesions. The proposed model incorporates a deep variant residual network and a squeeze-and-excitation module with an attention mechanism to solve the problem of feature extraction, which is difficult because of the dispersed locations of leaf disease. The accuracy of their model for various plant disease datasets ranged from 95.71% to 99.98%.

Karlekar and Seal [26] proposed a double module approach for classifying Soybean leaf diseases. The first module extracts leaves from the original image by subtracting the background. The second module introduces a CNN for plant disease recognition using segmented leaf images. The model achieved an accuracy of 98.14% on the PDDB dataset [27]. The limitation of this approach is that the diseased leaves were not photographed in a natural environment, so did not have complex interwoven leaves and the background used was uniform.

Classical deep learning solutions are too memory and time-consuming to be deployed on mobile devices that are the most used by farmers. Several researchers have suggested solutions for this issue. Ahmed et al. [28] proposed a lightweight transfer learning-based approach for the detection of diseases in tomato leaves. Their model uses an effective preprocessing method to enhance leaf images with illumination correction for improved classification. The model achieved an accuracy of 99.48% for ten tomato leaf disease classes in the PlantVillage dataset.

2) FIELD IMAGES MODELS

To solve redundant features, low contrast images, and long computational times issues, [29] proposed a single stream CNN architecture for the detection of citrus fruit diseases. Data augmentation was performed in the first step using four contrast enhancement operations, the MobileNet-V2 CNN model was selected and fine-tuned in the second step, and an improved Whale Optimization Algorithm was used in the third step to remove little redundant information from the second step. A total of 1,522 images of the augmented citrus fruits, leaves, and hybrid datasets were used in the experimental process, achieving accuracies of 99.4%, 99.5%, and 99.7%, respectively.

Because field-acquired images are impaired by complex backgrounds, uneven lighting, and densely overlapping leaves, state-of-the-art frameworks formulate the processing pipeline as a dichotomous problem (presence or absence of disease), whereas additional information regarding accurate disease localization and quantification is crucial for breeders. Garg et al. [30] propose a deep framework for the simultaneous segmentation of individual leaf instances and corresponding diseased regions using a unified feature map with a multi-task loss function for end-to-end training. The framework was tested on a field maize dataset with Northern Leaf Blight disease and the experimental results showed a disease severity correlation of 73% with manual ground truth data.

MaizeNet [31] was proposed as a model for the localization and classification of various maize crop leaf disorders. An improved Faster-RCNN was released. It utilizes the ResNet-50 model with spatial-channel attention as its base network for the computation of deep key points which are then localized and categorized into various classes. The proposed model was evaluated on the field condition dataset CD&S (Corn Disease and Severity) and attained an average accuracy score of 97.89% along with an mAP value of 0.94.

3) LABORATORY AND FIELD IMAGES MODELS

The use of image classification to accurately identify diseased regions corresponding to different disease types in individual plant leaves is limited. Phan et al. [32] used Simple Linear Iterative Clustering Segmentation on corn leaf images from the PlantVillage and Corn Disease and Severity (CD&S) datasets to create super-pixels, a cluster of pixels representing a region of interest on a corn leaf. Various pre-trained CNN were used to identify diseased regions corresponding to five super-pixel classes (healthy, northern leaf blight, gray leaf spot, common rust, and background) for the PlantVillage dataset and four super-pixel classes (northern leaf blight, gray leaf spot, northern leaf spot, and background) for the CD&S dataset. The results demonstrated that SLIC segmentation and deep learning helped to identify the presence of multiple disease regions in individual leaves under field conditions.

The complex background information of crop images from practical applications and insufficient training data can cause incorrect recognition of diseases using deep learning models. To address this challenge, Xiong et al. [33] proposed a method for identifying cash crop diseases by using automatic image segmentation and deep learning with an expanded dataset. An Automatic Image Segmentation Algorithm based on the GrabCut algorithm was designed to automatically remove image background while retaining the disease spots. 28% of the images in the dataset were added from the Internet and practical planting bases to expand the public PlantVillage dataset and improve the generalization ability of MobileNet. The images were processed by AISA before they could be used for disease features extraction to reduce the number of calculations. The experimental results showed 80% accuracy for 27 diseases in the six crops used for evaluation.

Leaf feature extraction is a key component of plant disease detection and classification. A hybrid model for plant disease classification based on a Transfer Learning-based model followed by a vision transformer is proposed [34]. Leaf feature extraction is performed in two consecutive phases: i) initial feature extraction using a pre-trained model, and ii) deep feature extraction using the ViT model. The results showed that TLMViT achieved an enhancement of 1.11% and 1.099% in validation accuracy and 2.576% and 2.92% in validation loss compared to the transfer learning-based model for the PlantVillage and wheat datasets respectively.

C. PROBLEM STATEMENT

Table 4 summarizes the literature review of various models and methods used for plant disease identification and classification.

We noticed that plant disease detection models on field images do not use publicly available field plant disease datasets such as PlantDoc or FieldPlant for experimentation. When the authors used self-collected images to evaluate their models, they were usually not available to others, making their results non-reproducible. Their research was usually conducted on a single specific plant disease making it ungeneralizable.

According to Li et al. [35] most of the Deep Learning frameworks proposed in the literature have good detection effects on their own datasets, but not on other datasets because of the models' relatively low levels of robustness. Therefore, more robust deep learning models are required to adapt to diverse disease datasets.

The purpose of this study is to propose a generic field plant disease detection and classification model that can improve the classification accuracy of various field plant disease datasets. The model should also allow for the detection of multiple diseases in the same plant leaf image.

III. SEGMENT ANYTHING MODEL FOR FIELD PLANT DISEASE DETECTION

Fig. 4 describes the model relying on Segment Anything Model for field-condition plant disease identification and classification. The model workflow is further described in the subsequent subsections.

TABLE 4. Summary of plant disease detection models.

No.	Ref.	Task	Dataset	Method / Model	Accuracy	Pros and Cons
1	[24]	Disease classification	PlantVillage	Attention-embedded residual CNN	98%	Lab images used for training
2	[25]	Disease classification	Various datasets	Advanced residual network and attention mechanism	95.71% 99.98%	Extracts more accurate ROI Laboratory images
3	[26]	Disease classification	PDDB dataset	Leaf extraction and classification	98.14%	Laboratory images
4	[28]	Disease classification	PlantVillage tomato leaf	Lightweight transfer learning	99.48%	Lightweight model Laboratory images
5	[29]	Disease classification	Citrus fruits Citrus leaves Hybrid datasets	Single stream CNN	99.4% 99.5% 99.7%	Dataset on only 1,522 images
6	[30]	Disease severity	Self-collected maize northern leaf blight	Unified feature map with a multi-task loss function	73%	Idenditfy disease severity in complex background images
7	[31]	Disease classification	Corn Disease and Severity	ResNet-50 model with spatial-channel attention	97.89%	Single plant used to evaluate the model
8	[32]	Disease classification	PlantVillage and CD&S corn leaf diseases	Simple Linear Iterative Clustering Segmentation	97.77%	Identify the presence of multiple disease regions on individual leaves Laboratory and field images used
9	[33]	Disease classification	PlantVillage Self-collected dataset	GrabCut algorithm for segmentation	80%	Complex background removed Laboratory and field images used
10	[34]	Disease classification	PlantVillage Wheat dataset	Transfer Learning-based model and vision transformer	98.4% 98.7%	Proper features extraction Laboratory and field images used

The proposed model uses PlantVillage as the foundation dataset for plant disease detection and classification. PlantVillage is the largest publicly available dataset for this task with 54,309 laboratory images spanning 14 crop species across 38 classes of plant diseases. The model's input images are then classified into one of 38 classes in Plantvillage.

The model splits the plant disease detection process into four steps: 1) The input field image is fetched to the Segment Anything Model (SAM) module which outputs all segmented leaves and background objects. 2) The discriminator takes the segmented objects as input and determines which are the actual leaves and which are not. 3) Among the identified leaves, the Region of Interest is selected as the leaf with the lowest anomaly score. 4) Final classification is performed on the identified ROI.

Before being used for inference, the model is trained in steps 0, 0.1 and 0.2. This preprocessing phase (0) consists of removing the backgrounds of various plant disease datasets images, namely Plantvillage, Fieldplant and Plantdoc. The resulting datasets leaves are used to train the FCDD discriminator to distinguish between leaves and backgrounds (0.2); specifically, the resulting *White Background Plantvillage* is used to train the final classifier CNN (0.1).

A. MODEL TRAINING PROCESS

We first considered the hypothesis that the background of plant images influences the accuracy of the classification tasks performed by neural networks. We initially separated the leaves from their background in the plant disease images. The first step in model training is to remove the Plantvillage, PlantDoc and FieldPlant image backgrounds to ensure that they do not influence the final classification in one way or the other because all image pixels are used during CNN training or running.

1) 0: PREPROCESSING

In step 0, to eliminate complex plant backgrounds, we ran the SAM model on the original Plantvillage, PlantDoc and FieldPlant datasets and obtained the masks of the different objects as the output. Image processing techniques were used to isolate each object identified in the image. Finally, the background objects were manually separated from the identified leaves. To simplify this process, we used a Python library that allowed us to identify the dominant color in an image [36]. Thus for each object identified in an image, if its dominant color was green the object was then classified by default as a leaf; otherwise, it was classified as a background. The final manual verification and correction were then made at the end. Algorithm 1 describes the overall process.

To avoid introducing bias into the data, images with very small sizes (lower than 125kb) considered to be leaves were eliminated during the manual verification phase. This algorithm resulted in 67,044 leaf (normal) and 107,958 background (anomalous) images.

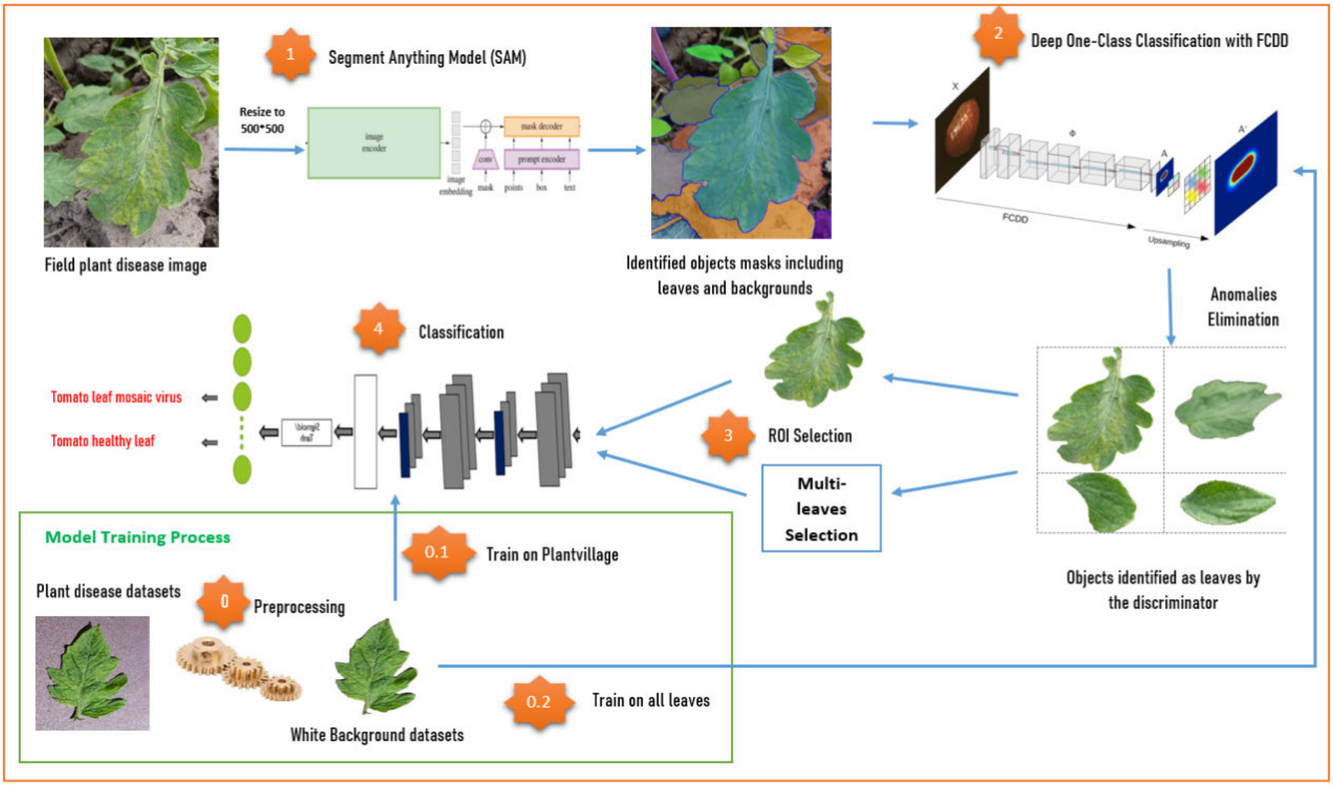

FIGURE 4. **Field plant disease classification model. 1) The input field image is fetched to the SAM module which outputs all the segmented leaves and background objects. 2) The discriminator takes the segmented objects as input and determines which ones are actual leaves and which ones are not. 3) Between the identified leaves the Region of Interest is selected as the leaf with the least anomaly score. 4) Final classification is done on the identified ROI.**

The normal images obtained from the Plantvillage dataset were released as a new public laboratory plant disease dataset, *While Background Plantvillage* [37], available on-line for researchers[1] on the Zenodo datasets platform. This dataset is used in the next step to train the final classifier.

2) 0.1: TRAINING THE FINAL CLASSIFIER WITH WHITE BACKGROUND PLANTVILLAGE

Given that the proposed model uses Plantvillage as the foundation dataset, the input field-condition image is classified at the end of the process as one of the 38 classes of plant diseases of the *White Background Plantvillage* dataset. We used this dataset to train the CNN to perform the final inference of our model. The CNN is based on MobileNetV2 and uses imagenet pre-trained weights. All input images were resized to (224 × 224 x 3) and the softmax activation function was used for classification. To avoid over-fitting, a dropout rate of 20% was applied, and Early Stopping was used as the regularization strategy. The Adam optimizer was used for training, and Categorical_crossentropy was used to compute the loss function. With fine-tuning, only the last 20 layers of the model were trained, and the model achieved a validation loss, accuracy, f1_score, precision and recall of 9.18, 97.63%, 97.67%, 98.12% and 97.24%, respectively.

[1]https://zenodo.org/records/10219622

3) 0.2: TRAINING FULLY CONVOLUTIONAL DATA DESCRIPTION (FCDD) FOR OUTLIER DETECTION

In Step 1, Segment Anything Model performs segmentation on the original input image and identifies all the objects, leaves, or backgrounds present in the image. To differentiate between the actual segmented leaves and background, a background-leaf discriminator that can differentiate a plant leaf from a background must be trained. To achieve this, we built an outlier detector, a Deep One-class CNN, trained on the *normal* dataset produced in Algorithm 1 that recognizes the objects of the *normal* class as target images, whereas any other image is identified as an outlier.

Deep one-class classification performs anomaly detection by learning a neural network to map nominal samples near a center c in the output space, causing anomalies to be mapped away. Fully Convolutional Data Description (FCDD) [17] is an explainable Anomaly Detection method in which the output features preserve spatial information and serve as a downsampled anomaly heatmap.

Fig. 5 shows the architecture of the FCDD outlier detector.

Outlier Exposure which describes the use of some anomalous samples during the training of a Deep One Class

Algorithm 1 Preprocessing the Datasets

Input: *Plantvillage*, *Plantdoc*, *FieldPlant*
Output: *normal*, *anomalous* ▷ Target and Outlier classes

$datasets \leftarrow \{Plantvillage, Plantdoc, FieldPlant\}$

for *dataset* in *datasets* **do**

for *image* in *dataset* **do**
▷ Segment image with Segment Anything Model to get all its objects
$objects \leftarrow segment\_anything(image)$

for *object* in *objects* **do**
▷ Check whether the dominating color is green
if $majorcolor(object) =' green'$ **then**
▷ object is probably a leaf
$normal \leftarrow normal + object$
else
▷ object is probably a background
$anomalous \leftarrow anomalous + object$

▷ We manually do checkings to correct mistakes

$normal \leftarrow check(normal, anomalous)$
$anomalous \leftarrow check(normal, anomalous)$

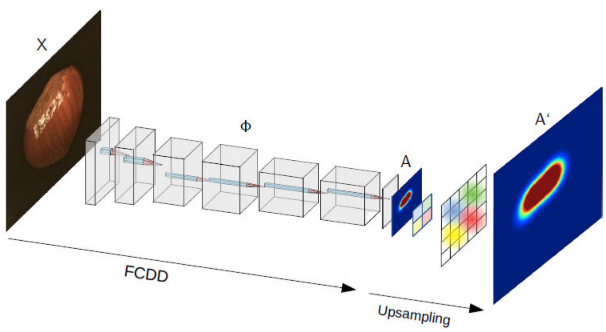

FIGURE 5. Overall procedure to produce full-resolution anomaly heatmaps with FCDD [17]. X denotes the input, ϕ the network, A the produced anomaly heatmap and A' the upsampled version of A using a transposed Gaussian convolution.

CNN has been shown to be very effective in increasing model accuracy [38]. FCDD is trained using samples labelled as nominal or anomalous produced by Algorithm 1.

Let $X_1, \ldots, X_n$ denote a collection of samples with labels $y_1, \ldots, y_n$ where $y_i = 1$ denotes an anomaly and $y_i = 0$ denotes a nominal sample. With a Fully Convolutional Network $\phi : \mathbb{R}^{c\times h\times w} \rightarrow \mathbb{R}^{u\times v}$ the FCDD objective utilizes a pseudo-Huber loss on the FCN output matrix (1)

$$A(X) = \sqrt{\phi(X, W)^2 + 1} - 1, \tag{1}$$

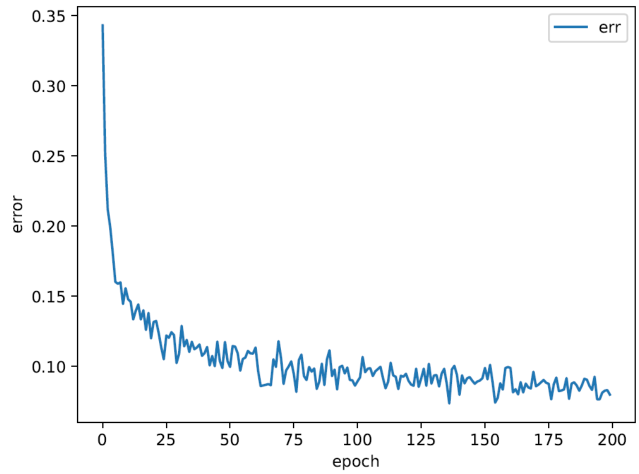

FIGURE 6. FCDD loss evolution during training.

where all the operations are applied in an element-wise manner. The FCDD objective function is then defined as (2), shown at the bottom of the next page.

$\|A(X)\|_1$ is the sum of all entries in $A(X)$, which are all positive. The objective maximizes $\|A(X)\|_1$ for anomalies and minimizes it for nominal samples; thus, we use it as the anomaly score. The entries of $A(X)$ that contribute to $\|A(X)\|_1$ correspond to the regions of the input image that add to the anomaly score. Fig. 10 shows the anomaly scores computed for some leaves and background objects produced by the SAM component from an input plant image.

The model reached a ROC Test Score of 0.9793 after training the model on 200 epochs using the 67,044 leaf images (as the normal class) and the 107,958 background images (for outlier exposure) produced by Algorithm 1. Fig. 6 describes the evolution of the model loss during training and Fig. 7 presents the model ROC test score.

B. MODEL RUNNING PROCESS

1) STEP 1: IMAGE SEGMENTATION WITH SAM

Segment Anything [16] was recently released by Meta AI Research as a promptable segmentation task, an image segmentation model (Segment Anything Model, described in Fig. 8), and the largest segmentation dataset to date, with over 1 billion masks on 11 million images. Segment Anything is a foundation model (trained on broad data at scale and adaptable to a wide range of downstream tasks [39]) for image segmentation. It is a promptable model that is pre-trained on a broad dataset using a task that enables powerful generalization. The model is designed and trained to be promptable, so that it can transfer impressive zero-shot performance to new image distributions and tasks.

In the proposed model, SAM is first used to segment the original field plant image and retrieve all the individual objects it contains without distinction. Text prompt is not used here to retrieve only leaves from the input images because SAM only performs a preliminary exploration of

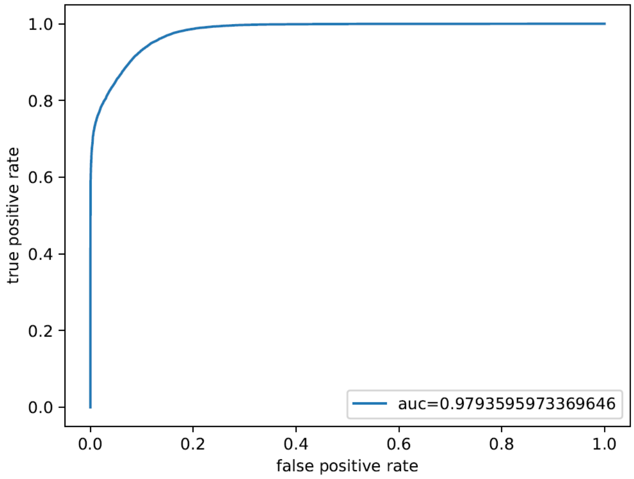

FIGURE 7. FCDD ROC Test Score.

text-to-mask prediction with low robustness [16]. Suitable parameters were selected so that all visible objects in the image (leaves, stems, fruits, ground, sky, etc.) could be identified and retrieved as masks. No discrimination is made between the segmented objects at this step. Fig. 9 shows an example of image segmentation using SAM.

2) STEP 2: LEAVES VS BACKGROUND DISCRIMINATION

All object masks (leaves, sterns, fruits, branches, background, etc.) segmented in Step 1 by SAM are retrieved as individual images from the original input image and fetched into the One-class CNN. This determines which objects are actual leaves and which are background with a ROC Test Score of 0.9793. The structure of this model is described in Subsection III-A3.

Fig. 10 shows the anomaly scores computed for the objects identified in the original image using SAM.

3) STEP 3: OBJECT OF INTEREST SELECTION

The Region of Interest can be a single leaf selected for the detection of a single plant disease class appearing on the original field plant image. In this case, we assume that the ROI for the disease detection task is the leaf with the lowest anomaly score. For this purpose, we sort the leaves identified in the previous step by ascending anomaly scores. The leaf with the smallest anomaly score is selected and used in the final classification step.

However, we may be interested in detecting multiple diseases in input image. In this case, the user specifies the number n of leaves they will like to classify and the n first objects with the lowest anomaly scores are then selected. These objects are then directly submitted to the classification CNN which will produce a specific output disease class for each input leaf.

4) STEP 4: FINAL CLASSIFICATION

The final step of the solution is the actual classification. The identified ROI is submitted as input to the classifier to determine its class for single disease detection or its classes for multi-disease classification. Classification is performed among the 38 classes of the *White Background Plantvillage* dataset.

It would not be interesting for the user to choose multi-disease classification in cases where there is not more than one significant leaf in the plant field image submitted as an input to the model. Indeed, the various other leaves could be of very low resolutions and areas, and may not allow for appropriate classification by the final classification CNN.

IV. RESULTS AND DISCUSSION

A. SYSTEM CONFIGURATION

The experiments were trained on a server with the following characteristics:5 GPU Tesla T4 with 16 GB RAM, 4 TB HDD, and 2 AMD EPYC 7251 CPUs with 512GB RAM. Experiments were performed using a GPU for faster training. Currently, there is an absence of a theory that can satisfactorily provide guidance in determining various hyper parameters within ANN algorithms [40]. To train the networks, we used the categorical_crossentropy loss because it is specifically designed to measure the dissimilarity between the predicted class probabilities and the true class labels. We chose learning rates of 0.001 for training and 0.0001 for fine-tuning. The learning rate determines the step size at which the weights of the network are updated during training. Choosing a low learning rate in CNN training has several advantages, including: training stability, precision, convergence and avoidance of overshooting. Transfer Learning was used to improve the accuracy of the models, and we present only validation metrics in the results. We used the weights provided in Keras trained on ImageNet for the pre-trained models. All the images were resized according to the CNN models before being fed into the network. Each experiment was conducted for over 250 epochs.

B. EXPERIMENTS SETUP

In our experiments, we used the original raw field-condition images from the PlantDoc [18] dataset. As described by our model, the original dataset images were first run on the SAM component to identify all objects. The objects were then subjected to the FCDD component to determine the actual leaves and backgrounds. The Regions of Interest we kept for

$$\min_{\mathcal{W}} \frac{1}{n} \sum_{i=1}^{n} (1 - y_i) \frac{1}{u \cdot v} \|A(X_i)\|_1 - y_i \log\left(1 - \exp\left(-\frac{1}{u \cdot v} \|A(X_i)\|_1\right)\right) \quad (2)$$

i

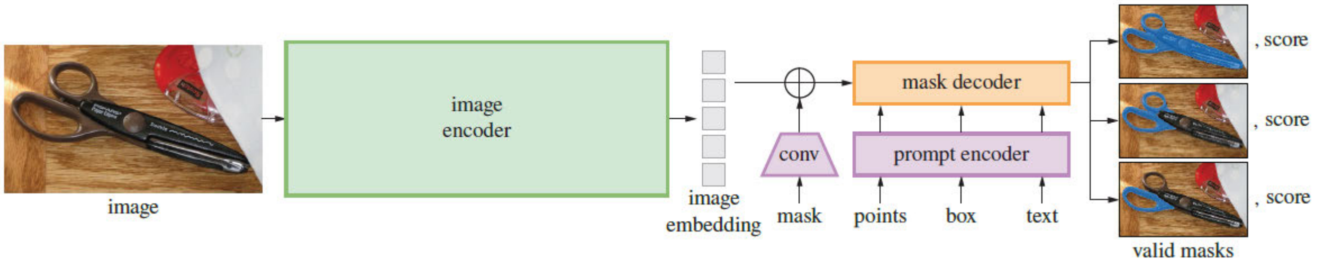

FIGURE 8. Segment Anything Model (SAM) overview. A heavyweight image encoder outputs an image embedding that can then be efficiently queried by a variety of input prompts to produce object masks at amortized real-time speed. For ambiguous prompts corresponding to more than one object, SAM can output multiple valid masks and associated confidence scores [16].

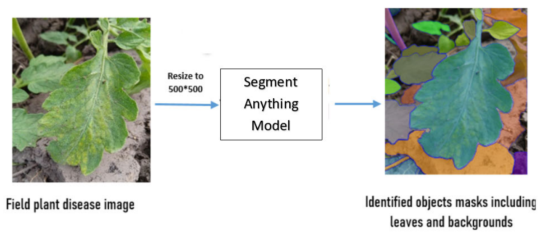

FIGURE 9. SAM Region Proposal. The model takes as input a plant field image and produces as output the masks of all the suggested regions (objects) identified in the image. 64 regions were suggested by the model in this example.

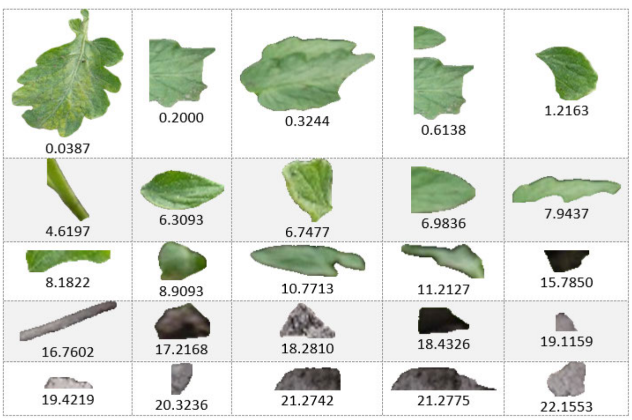

FIGURE 10. Anomalies scores computed by FCDD on input objects. We find that the more the object looks like a leaf the less its anomaly score is.

these experiments are, for all the objects present on an image, the ones with the least anomaly scores (those looking the most like a leaf). Finally, this process produced the same directory structure of disease classes as the original dataset, with each image having only one leaf and a white background. These datasets were then used as test sets for the various scenarios.

To evaluate our model, we ran various state-of-the-art classification CNN (InceptionResNetV2 [41], MobileNet [22], VGG16 [42], and InceptionV3 [43]) on the original and preprocessed datasets and compared the results. Given that we chose PlantVillage as the foundation dataset for our model, we evaluated the classification task on different field plant disease datasets with PlantVillage as the training set. First, the models were trained and evaluated without our model (using original field images). They were then trained with our model (using single white background leaf images). The results demonstrated the efficiency of the proposed approach.

C. RESULTS

1) Our model can properly identify various plant disease classes on the same input field plant image; the FCDD component produces as output the different objects identified in the original image along with their anomaly scores sorted in ascending order. The user specifies the number n of leaves they will like to classify from the image and the n first objects (with the lowest anomaly scores) are then used for inference. This result absolutely contrasts with the 38.9 and 14.4 mAP on the object detection task reached by PlantDoc [18] and FieldPlant [19], respectively.
2) Tables 5, 6 and 7 present various metrics of two different state-of-the-art CNN on the classification task on field plant disease images. When using our model we notice a significant improvement of the validation accuracies, up to 15% with InceptionResnetV2.
3) We share the open source code of the model on GitHub[2] for developers and researchers. They can explore the repository, which includes all source code and well-trained weights files for the Segment Anything Model, Fully Convolutional Description Model, and Mobilenet classification model.
4) In response to the critical need for efficient plant disease detection, we deployed an Algorithmic Agricultural Advice (AAA) model. The AAA model, deployed as a mobile app on Android[3] and iOS,[4] is designed to empower farmers to make informed decisions about their crops according to the detected diseases. By providing a plant image, specifying the number of leaves for prediction, and selecting their

[2]https://github.com/emmanuelmoupojou2/Field_Plant_Disease_Detection

[3]https://play.google.com/store/apps/details?id=io.ionic.itiad

[4]https://apps.apple.com/us/app/agri-care/id6476977628

TABLE 5. Classification tasks on field plant images without and with our model. We notice an improvement of all classification metrics when using the suggested model.

Classifier	Training set	Test set	Direct Classification(%)				Our Model(%)			
			Accuracy	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score
InceptionResnetV2	PlantVillage	PlantDoc	18.6	21.4	18.97	20.11	**29.15**	**29.37**	**28.16**	**28.75**
MobileNet	PlantVillage	PlantDoc	25.51	25.25	24.12	24.67	**29.62**	**30.26**	**27.53**	**28.83**

TABLE 6. Suggested model performances are further improved when using the two first objects with the least anomaly scores for final classification.

Classifier	Training set	Test set	Direct Classification(%)				Our Model(%)			
			Accuracy	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score
InceptionResnetV2	PlantVillage	PlantDoc	18.6	21.4	18.97	20.11	**30.59**	**30.76**	**28.27**	**29.46**
MobileNet	PlantVillage	PlantDoc	25.51	25.25	24.12	24.67	**32.69**	**33.2**	**31.92**	**32.55**

preferred language, farmers can gain valuable insights into the health of their crops and take appropriate countermeasures.

Table 5 shows an improvement of more than 10% of the validation accuracy when the suggested model is used for plant disease classification on field images. In some cases, as discussed in Subsection IV-D, the discriminator component misclassifies the leaf object we want, putting it in second or third position rather than the first position as expected (with the least anomaly score).

To capture these cases, we ran two other sets of experiments. First, we used the two objects with the least anomaly scores returned by the discriminator for the final classification. The classification is said to be correct if the class predicted by the model for one of these objects matches the expected class for the input image. The results of this experiment are presented in Table 6 where we notice a further improvement in the various classification metrics.

Second, we extended the objects of interest to three. Thus, the three objects with the lowest anomaly scores as returned by the discriminator were used for the final inference. The classification is said to be correct if one of the three predicted classes for these selected objects matches the expected class for the input image. In this configuration, Table 7 shows that the model performance continues to improve, with a 15% improvement in accuracy compared to direct classification.

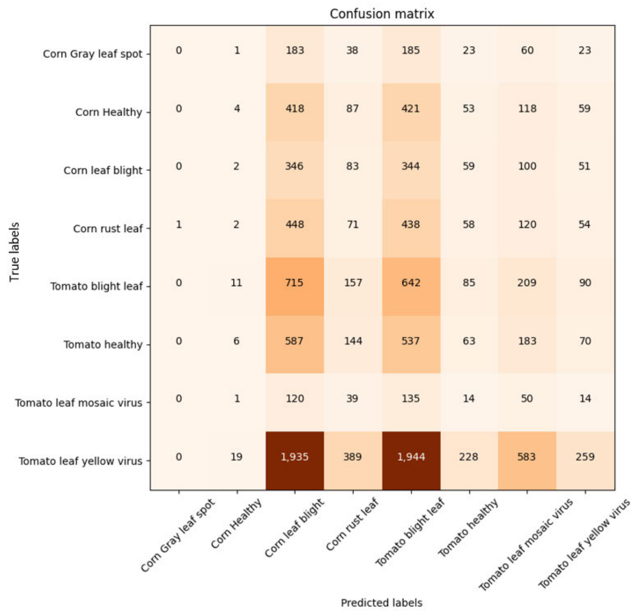

FIGURE 11. Confusion Matrix of the classification task on FieldPlant using our model.

D. FUTURE WORK

To mitigate negative transfer, task-specific fine-tuning was employed by further training and fine-tuning the model on the target task to adapt the knowledge transferred from ImageNet to the requirements of the plant disease classification task. To reduce the impact of negative transfer and encourage the model to learn task-specific features, a dropout rate of 20% was used as the regularization technique in all experiments. However, instead of transferring all the knowledge from the source task, specific components or layers of the network can be selected for transfer based on their relevance to the target task.

When tested on the FieldPlant dataset, the proposed model showed no significant improvement in the classification accuracy. Further investigation using the confusion matrix presented in Fig. 11 revealed that many tomato images were misclassified by the model. Indeed, FieldPlant image backgrounds are very dense and full of greenery. The resulting segmented objects were mistakenly considered by the model as leaves (with the lowest anomaly scrores), given that the FCDD component was trained only to recognize the normal

TABLE 7. Suggested model performances are further improved when using the three first objects with the least anomaly scores for final classification.

Classifier	Training set	Test set	Direct Classification(%)				Our Model(%)			
			Accuracy	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score
InceptionResnetV2	PlantVillage	PlantDoc	18.6	21.4	18.97	20.11	**33.46**	**34.73**	**33.05**	**33.86**
MobileNet	PlantVillage	PlantDoc	25.51	25.25	24.12	24.67	**34.32**	**35,22**	**33.78**	**34.48**

FIGURE 12. FieldPlant segmented background objects mistakenly classified as leaves by the model because of their density and greenery.

class, consequently decreasing the model's performance. Fig. 12 presents some of the background objects considered as leaves by the model because of their leaf-looking structure.

Further improvement of the model should differentiate dense greenery backgrounds from actual leaves. Image variance and contour detection are promising approaches.

V. CONCLUSION

This study presents a model ensemble solution to mitigate crop yield losses and promote sustainable agricultural practices. This model combines the Segment Anything Model (SAM) and the Fully Convolutional Data Description (FCDD) to accurately identify and classify plant diseases in field images. The model was shared on GitHub for researchers and a mobile app was developed for practitioners. The proposed model addresses the limitations of existing classification models by effectively handling the complex backgrounds, interwoven leaves, and varying lighting conditions present in field images. This study demonstrates that the proposed model outperforms existing classification models on public field plant disease datasets, such as PlantDoc, by improving the classification accuracy by more than 10%. By accurately circumscribing all identifiable objects in the image using SAM and FCDD for anomaly detection, the model effectively separates background objects from actual leaf objects, allowing for proper classification and enabling the detection of diseases appearing on individual leaves within the same image. However, the FCDD component should be able to distinguish between actual leaves and dense greenery backgrounds. On the other hand, investigating continual learning techniques can enable the model to adapt and learn from new data over time, allowing it to stay up-to-date with emerging diseases and variations in plant conditions. We believe that this model significantly furthers the agenda of plant disease detection and classification of field plant images.

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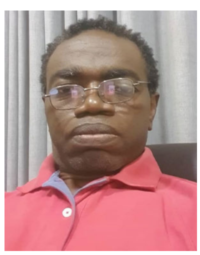

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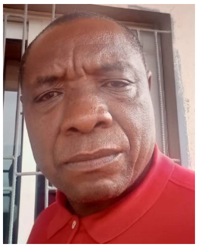

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