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A Method for the Detection and Reconstruction of Foliar Damage caused by Predatory Insects

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***Abstract*—Management of agricultural production and rural activities has been supported by recognizing machine learning patterns and algorithms, as in the automation of leaf analysis. However, leaf border damage compromises leaf structures, making it difficult to estimate the lost contours. Effects caused by predatory insects are difficult to be monitored by inspection processes, and the harmful results caused by them can deteriorate the performance of machine learning models. In this sense, plant leaves that are not fresh or intact are avoided. Consequently, the number of samples for use in training steps is reduced, leading to problems of data balancing and limited generalization models. This study presents an automatic method for reconstructing an injured leaf at a probable stage before defoliation. Thus, the reconstruction of damaged leaves can be used to maximize the number of samples in the plant species classification processes and provide visible results for the agronomic analysis of regions of occurrence of leaf damage and the components of the primary leaf structure affected by predatory insects. Based on the experimental results, we conclude that the proposed approach can accurately delimit the injured leaf silhouette and restore the leaf regions affected by herbivory attacks.**

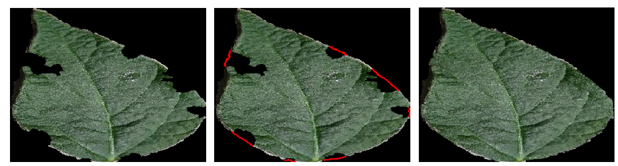
***Index Terms*—image restoration; insect predation; smart farming; precision agriculture; inpainting**

I. Introduction

Agriculture businesses move billions of dollars every year in many countries. In Brazil, agricultural activities were responsible for 21.4% of the Gross Domestic Product (GDP) in 2019 [1]. In 2020, Brazil surpassed the largest soybean producer in the world, the United States, with a production of 126 million tons with an average price of $409 per ton [2], [3]. In the same year, led by China and the United States, corn reached a record price of $362 per ton, something that has not been seen since 2015 [4]. The production of fresh deciduous fruits, such as apples, grapes, and pears, increased compared to previous years, and the production of stone fruits exceeded expectations in Turkey and European Union [5], [6].

Despite the promising results, world consumption of agricultural products is expected to increase significantly in 2021. In this sense, leaf analysis is one of the tasks that has generated helpful information for agricultural production and, consequently, meets global demand. As the leaf area is responsible for the photosynthesis process, the growth of the plants and the filling of the grains can be monitored through visual inspections of the state of the leaves, which enables more precise crop management as in the application of insecticide.

However, the effects caused by predatory insects are difficult to be monitored by inspection processes. Leaf damage in border regions compromises leaf structures, making it difficult to estimate the contours lost. In computer-based solutions, there are approaches for this task, but with some limitations. [7] developed a mobile application for the quantification of leaf herbivory that depends on the user's ability to interact with it and [8] developed a deep neural network model to estimate the level of defoliation but that requires several artificial simulations of leaf damage and a large number of images for the training stage.



(a) (b) (c)

Fig. 1. An overview of the proposed method. For an injured leaf (a), the boundaries of the damaged area are automatically traced (b), and the leaf shape is recovered (c).

Furthermore, the identification of plant species by computer generally ignores samples with marginal and severe damage to prioritize fresh and intact plant leaves [9], [10]. As the performance of machine learning classifiers can change due to samples with variations in leaf shape, color and texture caused by damage, leaf images are selected considering their original shape and appearance [11]. On the other hand, these classifiers require samples in sufficient quantity for each class in the data set, and the exclusion of samples can generate imbalanced data, also deteriorating the overall performance of the machine learning models [12]. Consequently, leaf reconstruction could significantly contribute to expanding the number of samples. In the classification of injured leaves, they could be reconstructed before the identification process, increasing the chances of an assertive classification [13].

In order to deal with the limitations of related works and contribute to this field of study, we developed a computational method to reconstruct the contours of the leaf edge and restore the foliar canopy. The proposed method does not depend on the user's expertise to obtain the desired results and uses few leaf samples to construct an image model. Besides, the proposed method provides visible results that allow the agronomic analyst to verify the regions of occurrence of leaf damage and the components of the primary leaf structure affected by predatory insects. Figure 1 illustrates the edge of a leaf

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being traced and the result of the reconstruction process for an initially damaged leaf.

This study presents an automatic method for reconstructing an injured leaf at a probable stage before defoliation. We focus on leaf edge restoration by structuring a method capable of determining the damaged area and reconstructing the damaged leaves to a similar format to the original one. The novelty of our method is that it uses computational vision and digital image processing techniques combined with geometric leaf properties and statistical measurements to present a simple, inexpensive, and robust solution that can effectively contribute to decision-making in cultivars.

Our main contributions are as follows:

- automatic detection of damaged leaves caused by insect herbivory;
- visual reconstruction of the damaged regions through artificial filling;
- a versatile approach that works properly in a variety of cultivars;
- a useful application to support agricultural management decisions based on foliar analysis.

The remaining organizational structure of this paper is as follows: Section II summarizes the related work. Section III presents the method provided in detail. Section IV describes the experiment setup as the database used, input parameters, and evaluation metrics. Section V provides experimental results and analysis. Finally, in Section VI, we draw our conclusions and suggest ideas for future work in this field.

II. Related Work

Computer-based techniques are often applied to fill missing or damaged regions in digital images. Restoration processes are used to recover images affected by natural degradation or when artifacts need to be removed with visual preservation of the original images. There are several useful image restoration applications [14], especially in precision agriculture, where they play a significant role in improving the quality of pictures obtained from unmanned aircraft, poor quality videotape, and blurred satellite images [15].

The detection of pest attacks on plants makes it possible to identify regions of damaged leaf areas, which is useful in the quantification of damage caused by insects and subsequent management and treatment of possible infestations [7], [8]. In leaf damage detection approaches, the compromised area is estimated so that the total leaf area can be recognized and the missing parts can be noted and analyzed.

In this sense, [16] developed an algorithm for the recognition of damage in oilseed rape leaves. [17] used digital scanners and image manipulation software to estimate the leaf surface area that was damaged by insect herbivory. [18] identified methodologies for estimating leaf border and defoliation percentage in soybean plantations. [7] developed a mobile application to quantify leaf damage using digital image processing techniques. Besides that, [8] used convolutional neural networks to estimate missing areas on injured leaves.

Among the works that are related to our study, the proposal prepared by [13] stands out. The authors investigated leaf reconstruction so that damaged leaves could be recovered to increase the sample number in constructing learning models. Although the results are promising, in this approach, the regions of foliar damage need to be indicated in the form of training masks. Therefore, leaves with damage on leaf edges may require the preparation of these masks manually, which is very laborious and tedious.

Unlike related works, our proposal was designed to work regardless of the type of cultivar. We show through experimental results that our method works on a variety of crops that are important for global trade, such as soybean, corn, and fresh deciduous fruits. Furthermore, the proposed method is fully automatic and requires only a few leaf samples to build an evaluation model. The method does not require specialized equipment and uses only digital images acquired by conventional RGB cameras. As performed in the related works, our approach also uses digital image processing techniques. In addition, we deal with restoring the leaf boundary and the leaf shape through manipulation and artificial filling of the compromised leaf area.

III. Methodology

Our pipeline for the reconstruction of damaged leaves consists of six cohesive steps that can be seen in Figure 2 whose descriptions are presented in the following sections.

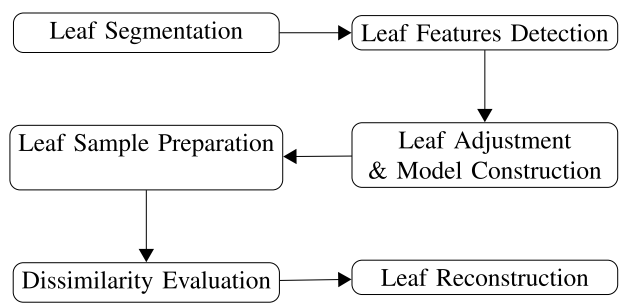

Fig. 2. Architecture components of the proposed method.

A. Leaf Segmentation

In this step, we apply a segmentation strategy to separate the leaf region from the image's background. Initially, in the original image, we apply an image filter through the median and average convolution processes, both with a kernel size equal to 5×5. Then, the Green channel of the RGB image is exceeded using an arithmetic operation in which the pixel values of the Green channel are doubled and subtracted from the Red and Blue channels ($\mathbf{G}' = 2\mathbf{G} - \mathbf{R} - \mathbf{B}$). Then, the Otsu threshold method [19] is applied, and the binary image obtained is used to exclude the non-leaf regions from the original image.

B. Leaf Features Detection

In this step, we identified leaf features from their geometric shape and morphological structure. Here, two approaches are employed. In the first, the interior pixels of the leaf is removed from the leaf area so that only the leaf outline, or border pixels, remain. Then the distance between these edge pixels is calculated using the Mahalanobis distance [20]. In this way, we find the two pixels most distant from each other, which allows us to draw a straight line that possibly indicates the central leaf vein. In the second approach, Sobel's edge detector [21] is applied over the Green channel of the original image, and a binary image is obtained. Then, this binary image is used to detect rectilinear shapes with the use of the Hough transform [22], which allows us to identify the other leaf veins, such as the lateral veins.

C. Leaf Adjustment and Model Construction

The leaf images are rotated to a position where the leaf tip possibly points up or down. We used the image features obtained in the previous step (straight lines) to check the inclination of the leaves and rotate them. After the rotation, the leaf area is identified and surrounded by a bounding box. Then, we crop the image, and the area outside the bounding box is deleted. Finally, the resulting image is resized to the original size of the initial image. This procedure creates a number of leaf models equal to the number of image features.

D. Leaf Sample Preparation

After positioning the input image into new positions and creating the collection of leaf models, some image templates are applied to each leaf model in order to simulate leaf area loss. Six templates are used to crop the left, right, top, and bottom areas of the leaf models, where the reference line (Section III-B) is used to guide the positioning of the templates into the images.

One of the templates removes 50% of the leaf area to the left of the reference line. Three other templates remove 50% right, 50% above, and 50% below, respectively. The other remaining templates remove 25% on both the left and right sides of the leaf, while the other removes 25% on both the upper and lower sides. After this process, the leaf area is detected to select the region of interest and guide the cropping and resizing of the foliar area. Thus, six damaged leaf samples are associated with each leaf model $\mathbf{w}_r \in \mathbf{W}$.

E. Dissimilarity Evaluation

The previous four steps are repeated for all images contained in a given healthy leaf image database, and the first three steps are also applied for the damaged input leaf. Each image generated from the damaged input leaf is compared to the leaf models and their damaged samples. Then, the estimated costs are associated with the comparisons made.

This comparison is performed by measuring the dissimilarity between the distributions of the damaged leaf area with the prepared models and samples. The earth mover's distance[1] (EMD) [23] is used, and the dissimilarities between them quantify the proximity between the damaged leaf to the image models. To perform this evaluation and in addition to the EMD[2], we propose a cost function that not only evaluates the correspondence between image pairs (of size $n \times m$) using their dissimilarities but also evaluates the non-overlapping areas between them.

The three terms of Eq. 1 describe the proposed cost function

$$Cost = \omega_1 + \omega_2 + \omega_3, \tag{1}$$

where

$$\begin{aligned}
\omega_1 &= EMD(\mathbf{I}_a, \mathbf{I}_b) \\
\omega_2 &= \psi + \zeta + \phi \\
\omega_3 &= \nu + \tau
\end{aligned}$$

and

$$\begin{aligned}
F(\mathbf{I}_a, \mathbf{I}_b) &= \frac{1}{nm} \sum_{i=1}^{n} \sum_{j=1}^{m} (p_{ij} \wedge q_{ij}) \\
F_A(\mathbf{I}_a, \mathbf{I}_b) &= \frac{1}{nm} \sum_{i=1}^{n} \sum_{j=1}^{m} (p_{ij} \vee q_{ij}) \wedge \neg(p_{ij} \wedge q_{ij}) \\
\psi &= F_A(\mathbf{I}_a, \mathbf{I}_b) \\
\zeta &= F(\mathbf{I}_a, \neg\mathbf{I}_b) \\
\phi &= F(\neg\mathbf{I}_a, \mathbf{I}_b) \\
\nu &= F(\neg\mathbf{I}_b, \mathbf{w}_r) \\
\tau &= F(\mathbf{I}_b, \neg\mathbf{w}_r)
\end{aligned}$$

where ψ is a function that calculates the area that is outside of the intersection between a damaged leaf model ($\mathbf{I}_a$) and the damaged input leaf ($\mathbf{I}_b$); ζ calculates the area that is in the damaged leaf model but not in the input leaf; ϕ calculates the area that is in the input leaf but not in the damaged leaf model; ν calculates the area that is in the healthy leaf model ($\mathbf{w_r}$), corresponding to the damaged leaf model $\mathbf{I}_a$, but not in the input leaf ($\mathbf{I}_b$); τ returns the area that is in the input leaf but not in the healthy leaf model.

Then, with the cost resulting from the comparison performed, the leaf model that has the smallest error is the chosen one, Eq. 2.

$$e = \arg\min\,(Cost), \tag{2}$$

where e is the minimum error resulting from the cost function between the damaged leaf and all leaf models.

F. Leaf canopy reconstruction

In this step, the retrieved image model and the damaged input leaf are converted to a binary image. In Eq. 3, logical conjunction is applied to the binary image $\mathbf{A}$ (damaged input leaf) and $\mathbf{B}$ (retrieved image model), resulting in $\mathbf{L}$, a logical image with the missing areas.

$$\mathbf{L} = \neg\mathbf{A} \wedge \mathbf{B} \tag{3}$$

To reconstruct the damaged leaf, a multiresolution pyramid approach is applied, referred to as image blending. This technique aims to improve spatial and color consistencies between a source (retrieved model) and a target image (damaged leaf) by using the resolution band independently, resulting in a

[1] It is also referred to as the Wasserstein distance and the Monge-Kantorovich problem.

[2] We use the code provided by [24] to calculate the earth mover's distance.

multiresolution mixing that focuses on generating a realistic image given the composite ones [25]. Also, we look at the image reconstruction through interpolation strategies in which an injured leaf is restored based on the values in undamaged areas. Image inpainting techniques are representative examples of this approach and belong to the area of digital image processing. In this study, we use the technique proposed by [26].

IV. Materials and Methods

A. Database

To evaluate the proposal, we consider some crop species available in the public database prepared by [27]. It is a diverse data set of leaf images obtained in various lighting conditions, including healthy and disease-affected leaves. From this database, we evaluate the proposed method considering 12 types of cultivars: Apple, Blueberry, Cherry, Corn, Grape, Peach, Bell Pepper, Potato, Raspberry, Soybean, Strawberry, and Tomato. The size of the images is 256×256.

B. Experiment setup

In the evaluation, we consider only images of healthy leaves, which are transformed by an automatic synthetic defoliation method elaborated by the authors. Our defoliation approach consists of extracting bite signatures from actual cases and preparing templates of foliar damage to promote different levels of leaf deformation. It receives a healthy leaf as input and returns a damaged leaf and its level of defoliation.

Each crop species of the database is divided into two groups, (i) data modeling and (ii) test data, selected randomly from the number of images in the database. The first one is used to construct the leaf models, and the second one is used to validate the proposal. The artificial defoliation is applied only to the test data group to sample damaged leaves at different levels from 1 to 30% deformation. Also, 42 images are used in the data modeling group and 30 images in the test data group for each 12 crop species under investigation.

C. Evaluation Metrics

The Structural Similarity Index (SSIM) [28] is used in the tests in order to quantify the image quality and to measure the similarity between the reconstructed leaves with their corresponding ground truth images. SSIM is standardized because the results are presented on a scale ranging from only -1 to 1, where a score closer to 1 means that the two images are very similar.

The SSIM quality assessment index is a multiplicative combination of luminance, contrast, and structural terms. The overall index (Eq. 4) is a multiplicative combination of measures of location and dispersion and regularization constants.

$$SSIM(\mathbf{T}, \mathbf{Y}) = \frac{(2\mu_t\mu_y + C_1)(2\sigma_{ty} + C_2)}{(\mu_t^2 + \mu_y^2 + C_1)(\sigma_t^2 + \sigma_y^2 + C_2)}, \tag{4}$$

where μ_t, μ_y, σ_t, σ_y, σ_{ty} are the local means, standard deviations, and cross-covariance for images $\mathbf{T}$ (ground truth) and $\mathbf{Y}$ (reconstructed leaf). C_1 and C_2 are regularization constants that are used to avoid instability for image regions where the local mean or standard deviation is close to zero. Furthermore, the average SSIM value for the test data set is:

$$\overline{SSIM} = \frac{1}{N}\sum_{i=1}^{N} SSIM(\mathbf{T}_i, \mathbf{Y}_i) \tag{5}$$

where N is the number of samples in the test data set.

In order to assess the texture of the reconstructed leaves concerning ground truth images, entropy is used. It is a statistical measure of randomness, which is defined as [29]:

$$E(\mathbf{I}) = -\sum_{k=0}^{L-1} p(k)\log_2(p(k)), \tag{6}$$

where $\mathbf{I}$ is the original image, $p(k)$ is the probability of occurrence of the value k in the image $\mathbf{I}$, and $L = 2^q$ indicates the number of different intensity levels in a digital image, in our case $q = 8$.

From Eq. 6, the Root Mean Square Error (RMSE) is used to evaluate the difference between the entropy values of the ground truth images and the reconstructed leaf using blending and inpainting techniques (Eq. 7).

$$RMSE(eT, eY) = \sqrt{\frac{\sum_{i=1}^{N'}(eT_i - eY_i)^2}{N'}}, \tag{7}$$

where $\{E(\mathbf{T}_1), \cdots, E(\mathbf{T}_{N'})\} \subset eT$ and $\{E(\mathbf{Y}_1), \cdots, E(\mathbf{Y}_{N'})\} \subset eY$, and N' is the number of images in the test data group ($N' = 30$). As opposite to SSIM, lower RMSE values indicate a better fit [30].

V. Results and Discussion

In our proposal, leaf reconstruction is a process that approximates an image with leaf damage to a healthy leaf. The harmonization between these images, in terms of image blending or image inpainting, allows us to create a visual representation in which an injured leaf is recovered at a stage before defoliation.

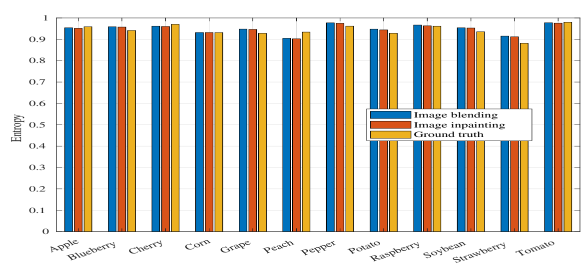

Fig. 3. Leaf reconstruction evaluation: Entropy scores.

In evaluating leaf reconstruction, we compared the reference images (ground truth) with the two digital image processing techniques that were selected for this study, image blending and image inpainting. The results pointed to a slight improvement in the reconstruction process by interpolating images, but not far from the other model under analysis. The image blending obtained $\overline{SSIM}$ values from 24% to 63% and the image inpainting from 24% to 64%.

TABLE I
LEAF RECONSTRUCTION EVALUATION: $\overline{SSIM}$ SCORES.

		Apple	Blueberry	Cherry	Corn	Grape	Peach	Pepper	Potato	Raspberry	Soybean	Strawberry	Tomato
Blending (%)	μ	24.2	37.9	52.0	63.7	51.3	36.8	40.1	40.3	43.4	32.7	46.4	31.0
	σ	07.0	06.4	09.9	12.0	06.7	11.9	05.0	08.6	07.4	04.4	05.4	08.6
Inpainting (%)	μ	24.2	37.6	52.5	64.2	51.8	36.8	40.2	40.6	44.0	33.0	46.4	31.2
	σ	07.3	06.5	10.0	12.5	06.8	11.9	05.2	08.8	07.0	04.6	05.6	08.9

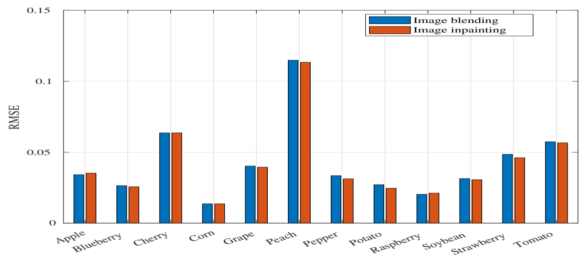

Fig. 4. Leaf reconstruction evaluation: RMSE scores.

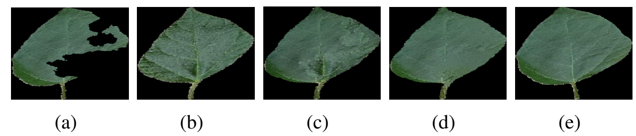

Fig. 5. Leaf reconstruction examples: (a) Damaged leaf, (b) the best matching model, (c) reconstruction with image blending [25], (d) reconstruction with image inpainting [26], (e) ground truth.

Table I presents the average SSIM obtained by each of the 12 cultivars observed in this study. The proposed method obtained the best results with corn leaves, reaching an SSIM value equal to 64%. Cherry and grape also showed promising results with values of 52% and 51%, respectively. The other cultivars, despite the diversity of samples and diversified lighting, achieved results above 24%.

Figure 3 shows the average $Entropy$ scores for each crop species in which the values listed correspond to the statistical properties of the reference images ($\mathbf{T}$) and the retrieved model or reconstructed image ($\mathbf{Y}$). The results show that the entropy of the reference images is very similar to those obtained with the leaf reconstruction process. Besides, it shows no significant difference between the techniques employed since the entropy values for the image blending and image inpainting is close and above 90%. Figure 4 points out that the difference between the entropy of the reconstructed leaves and the ground truth is minimal.

In a visual inspection, we observe that the proposed method can accurately delimit the injured leaf silhouette. The damage in border regions is recovered, making it possible to identify the areas where insect predation occurred. Comparing the image reconstruction techniques, we observe that the image blending better preserved the leaf vein structures while the image inpainting smoothed the reconstructed regions, making the perception of the leaf veins unfeasible. In contrast, image inpainting achieved the lowest error and some improvements over image blending, which indicates that other image inpainting techniques can be investigated in future work.

Figure 5 presents an example of a damaged leaf and the image model that best matched it, as well as the reconstructed leaves after image blending and inpainting techniques. Figure 6 shows a sample of each crop species with visible results achieved after the application of the proposed method using image inpainting. It is important to note that even for low SSIM values, the image reconstruction process correctly fills the regions of leaf damage.

VI. CONCLUSION

In this study, we present an automatic method for reconstructing an injured leaf at a probable stage before defoliation. We focus on the problem of leaf edge restoration by structuring a method capable of reconstructing damaged leaves to a format similar to their original shape. The results achieved point to a satisfactory reconstruction in which the damaged leaf edge can be effectively recovered. In addition, the injured leaf area can be filled, allowing visual analysis of the regions affected by herbivory. In evaluating leaf reconstruction, the method achieved results above 40% for most of the types of cultivar understudy and an SSIM value equal to 64% for corn leaves. In this sense, the proposed method can contribute to the monitoring of crops as well as to maximize the usefulness of images by increasing the number of individual samples of leaves.

As part of future work, our intentions include testing this method on other databases and other crop species, applying other leaf deformation models as natural defoliation, and using the proposed method with other digital image processing techniques for image reconstruction, especially other methods based on inpainting and deep learning approaches.

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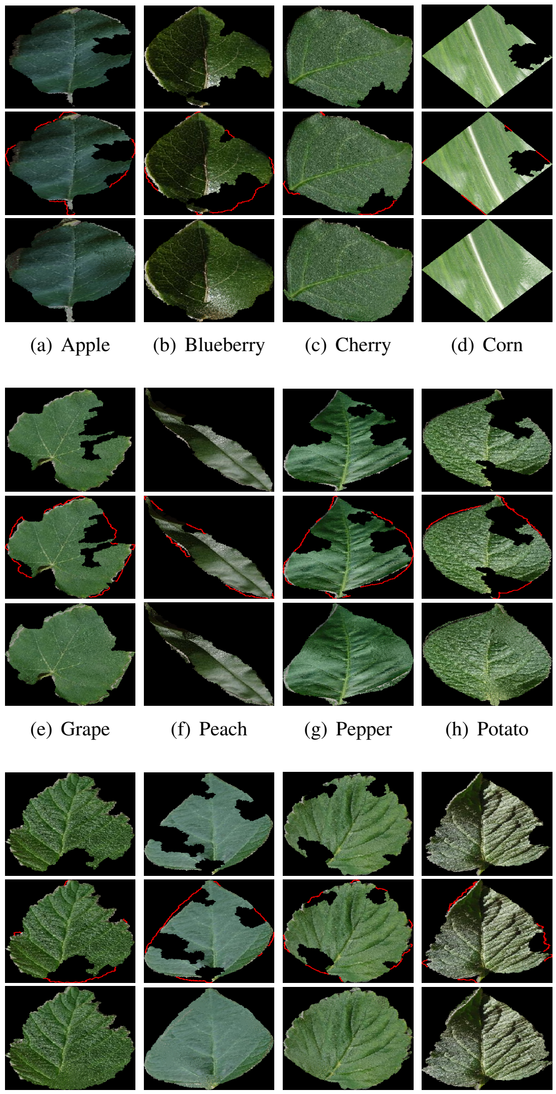

(a) Apple (b) Blueberry (c) Cherry (d) Corn

(e) Grape (f) Peach (g) Pepper (h) Potato

(i) Raspberry (j) Soybean (k) Strawberry (l) Tomato

Fig. 6. Edge restoration and leaf reconstruction of the area consumed by predatory insects using inpainting.

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