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Scientific articles

Aprendizaje para obtener la medición del costo computacional de los algoritmos de reconocimiento de imágenes en hojas del cultivo de soya

Learning to obtain the measure of computational cost of the image recognition algorithms in leaves of the soybean crop

Aprendendo a medir o custo computacional de algoritmos de reconhecimento de imagem em folhas de soja

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Resumen

El objetivo de este trabajo fue presentar la medición del costo computacional de varios algoritmos de reconocimiento de imágenes en hojas de soya, a través de un enfoque cuantitativo y experimental. Después de revisar la base teórica, se procedió a la implementación y experimentación de estos algoritmos utilizando imágenes de hojas de soya. Los resultados demuestran que no se puede establecer claramente cuál es la mejor elección entre los algoritmos detectores de descriptores como SIFT y SURF, pues mientras uno de ellos tiene un mayor tiempo de procesamiento en milisegundos, su consumo de memoria es menor, y viceversa. Por otro lado, en cuanto a los algoritmos de búsqueda de esquinas, como Harris y Shi-Tomasi, este último demostró ser superior tanto en términos del número de córneres detectados como en el tiempo de procesamiento en milisegundos y el consumo de memoria. Finalmente, en el grupo de algoritmos de contornos activos, se observó que el algoritmo Snake supera al Chan-Vese con un menor tiempo de procesamiento en milisegundos y un menor consumo de memoria. En síntesis, se puede sugerir que, para el reconocimiento de hojas en plantas de soya, el algoritmo Shi-Tomasi podría ser una opción adecuada debido a su desempeño óptimo en cuanto al tiempo de procesamiento y al consumo de memoria en comparación con los otros algoritmos analizados.

Palabras clave: algoritmos, reconocimiento de imágenes, costo computacional.

Abstract

The objective of this paper is to present the measurement of the computational cost of some image recognition algorithms in soybean leaves based on the experimentation of these algorithms. It is a quantitative and experimental study. Starting from a search of the theoretical foundation of the algorithms, the implementation and experimentation of these algorithms tested with images of soybean crop leaves was carried out.

As for the results obtained, it is found that between the descriptor detection algorithms SIFT and SURF in obtaining descriptors for each image tested there is no clear choice because while one has more processing time in milliseconds, its memory consumption is lower and vice versa. In relation to the Harris and Shi-Tomasi corner search algorithms, there is one that clearly shows that it is better both in the number of corners detected, as well as the time in milliseconds is less and the memory consumption is also lower, in this case it is the Shi-Tomasi. And among the active contour algorithms we have that both the Snake and Chan-

Vese algorithms, among them the one with the best response time is the Snake with less time in milliseconds and less memory consumption.
Summarizing the results, it can be suggested that the Shi-Tomasi algorithm for the recognition of leaves in soybean plants would be adequate since it obtains optimal results in terms of time and memory consumption of the computer equipment in comparison with the other mentioned algorithms.

Keywords: Algorithms, image recognition, computational cost.

Resumo

O objetivo deste trabalho foi apresentar a mensuração do custo computacional de diversos algoritmos de reconhecimento de imagens em folhas de soja, através de uma abordagem quantitativa e experimental. Após revisão da base teórica, procedemos à implementação e experimentação desses algoritmos utilizando imagens de folhas de soja. Os resultados mostram que não se pode estabelecer claramente qual a melhor escolha entre algoritmos detectores de descritores como SIFT e SURF, pois embora um deles tenha maior tempo de processamento em milissegundos, seu consumo de memória é menor, e vice-versa. Por outro lado, no que diz respeito aos algoritmos de busca de cantos, como Harris e Shi-Tomasi, este último mostrou-se superior tanto no número de cantos detectados como no tempo de processamento em milissegundos e no consumo de memória. Por fim, no grupo de algoritmos de contorno ativo, observou-se que o algoritmo Snake supera o Chan-Vese com menor tempo de processamento em milissegundos e menor consumo de memória. Em resumo, pode-se sugerir que, para reconhecimento de folhas em plantas de soja, o algoritmo Shi-Tomasi poderia ser uma opção adequada devido ao seu ótimo desempenho em termos de tempo de processamento e consumo de memória em comparação aos demais algoritmos analisados.

Palavras-chave: algoritmos, reconhecimento de imagens, custo computacional.

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Introduction

Soybean is a grass-type, upright, annual shrub with branches, whose height varies between 30 centimeters and 2 meters, and its life cycle can range between 80 and 200 days, depending on the variety and environmental conditions. Both the pods, stems and leaves of this plant are pubescent, that is, they are covered with villi. In addition, its seeds are spherical in shape, medium in size and contain high levels of oils and proteins. In improved soybean varieties, these figures can reach up to 40% protein and 22% oil in relation to their dry weight (Rosas and Young, 1991). Soybean, in fact, is the most extensive oilseed crop in the world, as there are around 130 million hectares of land that produce a total of 360 million tons (Roján-Herrera *et al*., 2022).

However, like any other crop, soybean is vulnerable to pests—such as leafhoppers, suckers, and scrapers (Magallanes-Estala *et al.*, 2014)—and damage caused by insects can have a significant impact on yield. and the quality of the harvest. The magnitude of this threat varies from one growing period to another, depending on factors such as the environment, the type of insects present, geographical location and climatic conditions. Therefore, it is recommended to carry out periodic visual inspections to detect possible infestations (Magallanes-Estala *et al.*, 2014).

Now, when it comes to image recognition, in the context of computer vision, it can be defined as "the ability of *software* to identify objects, places, people, writing and actions in images. Computers can use computer vision technologies in combination with a camera and artificial intelligence *software* to achieve image recognition" (Ramírez-González *et al.*, 2009).

In the case of soybean leaves, knowing which is the best algorithm for their recognition not only directly impacts agricultural productivity, but can also drive technological progress, sustainability and efficiency through computer solutions that benefit this sector. Therefore, the purpose of this work is to evaluate the computational cost of the SIFT, SURF, Harris, Shi-Tomasi, Snake and Chan-Vese algorithms through their comparison in the image recognition process of soybean plants. For this, the following hypothesis is proposed:

- The computational cost varies when using different image recognition algorithms for the detection of soybean plant leaves.

In this sense, the research question formulated was the following:

- What is the computational cost of the SIFT, SURF, Harris, Shi-Tomasi, Snake and Chan- Vese algorithms in image recognition of soybean plants?

Methodology

In the first section of the methodology section, previous work related to the recognition of soybean leaves is described. The second section sets out the key definitions necessary for a complete understanding of the article. Next, in the third section, some image recognition algorithms that can be applied in soybean cultivation are presented. Finally, the fourth section describes the experiments carried out.

Related jobs

Regarding the background, Larese *et al.* (2011) developed a methodology that uses image analysis of soybeans to detect the amount of chlorophyll in plants, which serves as an indicator of the physiological quality of the seeds. This approach also allows the classification and identification of different varieties of soybean crops through an automated leaf image recognition system.

In another study—conducted by Cáceres-Flores *et al.,* (2015)—it is mentioned that there are specialized works in image processing for pest detection and morphological analysis of plants in greenhouse crops. According to the authors, color differences between the leaves of healthy and infected plants can be detected to potentially identify the presence of pests through image segmentation.

the early detection of pests in pepper plants has been investigated using the RGB color model to process images and examine the characteristics of the leaves and stems. In this way, pests can be identified by grouping the images by color based on the symptoms of disease or infestation (Canty, 2019).

Likewise, a pest detection system has been implemented through image processing in the cultivation of sugar cane (*Begonia semperflorens)*. Specifically, Lin *et al*., (2017) have investigated the use of drones for photographic inspection of the sugarcane harvest, which represents a valuable contribution to this field.

Definitions

According to the Royal Academy of Engineering (sf), computational cost refers to the value in memory and execution time of an information system, application, etc., at the *hardware*, *software*, and maintenance level. On the other hand, for the Royal Spanish Academy (sf) an image (from the Latin *imago*) is a visual representation that shows the appearance of a real or imaginary object. There are two main categories of images: "mental" images, which people do not perceive but exist within them, and "created" or "repeated" images, which visually represent an object through various methods, such as drawings, paintings, photographs, or videos.

In a more specialized context, an image is generally defined as a two-dimensional function f (x, y) that represents the intensity of light, where "x" and "y" represent the spatial coordinates of a point, while f (x, y) is the intensity or gray level of the image at that point. When the spatial coordinates are finite and the amplitude covers a finite range of values, it is called a "digital image" (Sánchez-Prieto, 2014), which is a two-dimensional representation of an image that uses bits, that is, the smallest units of information made up of binary digits (0 and 1). Computers and other digital devices employ digital images, which can be defined mathematically as a two-dimensional function f (x, y), where "f" and the values of (x, y) are finite discrete quantities that represent a specific pixel value. within the image (Peña-Peñate *et al.*, 2016).

A digital image can be represented by a matrix f (x, y) size M x N as below manner:

$$f(x,y) = \begin{bmatrix} f(0,0) & f(0,1) & f(0,N-1) \\ f(1,0) & f(1,1) & f(1,N-1) \\ f(M-1,0) & f(M-1,0) & f(M-1,N-1) \end{bmatrix}$$

The matrix elements (pixels), in a typical monochrome image (operating in gray levels), have 2, 8 or 256 of intensity, for the that f(x, y) can vary of 0 to 255 (0 is black and 255 means white); This is what can be represented as a character in the majority of the idioms of programming.

An algorithm, on the other hand, is defined as a set of steps that, when performed correctly, lead to a result (Gómez-Fuentes *et al.*, 2014). According to image recognition, it refers to the classification of different image objects based on their descriptors. Objects detected with similar descriptors are grouped into a class (Fernández-García, 2012). The computational cost of an algorithm refers to the amount of time required to complete some operation; Likewise, it also has to do with the RAM memory used to perform said task (Trefethen and Bau, 1997).

Having explained the above, it is important offer a list and a comparison of algorithms for measure his cost computational, which would allow choosing the best option according to cost and reliability.

Image recognition algorithms

In the field of artificial vision, one of the problems classics is that of recognition or classification of images, that consists basically in take a either a set of images as inputs to generate as output an appropriate label for said images. In the case of leaves soybean, the objective is to predict if it is a soybean leaf, if it has a pest and what type of pest it has.

To carry out this task, the first step is to investigate and test various algorithms that help in its execution. In the field of artificial vision, there are numerous techniques that vary depending on the objectives to be achieved. Some of them are the following: feature-based methods that detect corners and spots, and vectors descriptive that HE extracts around of the neighborhood of those points. In addition, there are machine learning approaches through which the characteristics of the training data, that is, depending on the problem, the technique is chosen (Le, April 12, 2018; Mallick, 2016).

List of algorithms of Recognition of patterns

The algorithms linked to computer vision and pattern recognition are very diverse and encompass many techniques and objectives (Rivera-Díez, 2015). Next, we will proceed to name and explain different algorithms for detecting features in an image.

SIFT (Scale Invariant Features Transform)

The SIFT (Scale Invariant Features Transform) is a computer vision algorithm—originally released in 1999 by David Lowe —that is responsible for selecting salient features in grayscale images. From these, an image can be identified in the database and another larger one with a different number of elements arranged in a disordered manner (Ñauñay-Ilbay and Tipantuña -Córdova, 2013). He algorithm described by Lowe consists of four stages:

- Scale-space boundary detection: In this stage, points of interest are searched for the entire image and all scales are considered using the Gaussian difference.
- Precise location of the key point: For each point of interest above the model is adjusted to define its location and scale. Likewise, feature points (keypoints) are chosen, except those

that are close to the edges or have low contrast.

- Direction Assignment: Each base point is assigned one or more directions based on the direction of the local gradient. This orientation, together with the previously calculated position and scale, allows the descriptor to be invariant in these three cases.
- Description of key points: Local image gradients are measured around each feature point and its histogram is used to obtain an image of that region that is robust to significant light changes and small shape distortions (Cheerful and Fernández-Robles, 2016).

SURF (Speed Up Robust Feature)

The SURF algorithm (Speed Up Robust Features) is other detector of variables local. Was _ presented by first time by Bay *et al.,* (2006) and is based in the descriptor SIFT, although presents someprogress like the following:

- Higher calculation speed without performance deterioration.
- When there is a transformation of the image, it presents greater firmness.

Advances in this area are feasible because they allow the reduction of the complexity of the calculation and the dimensionality of the characteristic vectors of points of interest achieved, although it remains different and repetitive (Aracil-López, 2012). TO Below are listed the stages in the which is divided:

- Location of points of interest key points.
- Fixation of the orientation.
- Extraction of the descriptors.

Harris Corner Detector

The Harris detector is based on finding corners. These features are very insensitive to changes in rotation and scale. Corners are regions in an image with intensity variations in different directions, which represents the basis for finding the Harris point. Filtering the image with a moving window in eight directions, they get three guys of region (Enebral-González, 2009). TO continuation, they indicated the stages in the that it divides:

- For each pixel (x, y) calculate the matrix of autocorrelation.
- Build the variations map for each pixel (x, y).
- Thresholding is applied to the intensity map.
- Carry out suppression of non-maximums for find maximums local.

Shi-Tomasi cornes Detector

In 1994 J. Shi and C. Tomasi made small modifications and achieved better results than with the Harris Corner Detector. This algorithm proposes the following changes compared to the previous one (Rivera-Díez, 2015).

$$R = \min\,(\lambda_1 \lambda_2)$$

If the value obtained is greater than the threshold value, it means that they are in a corner. If the schematic drawing is drawn again, it means that it is found with the following figure, in which you can see simple view that only is considered corner when the values $\lambda_1\ y\ \lambda_2$ are find both by on of λ_{min}

List of algorithms of contours assets

Active contour models with semi-automatic representation of objects in images attempt to model the energy functions associated with these forces (external and internal) to develop curves guided by external forces and by limits and forces associated with the image. Typically, these models are based on edge detection using information collected from image gradients (Jiménez-Carretero *et al.*, 2011).

Active contours (Snakes)

In 2000, Ntalianis *et al.*, wrote an algorithm to automatically obtain the initial contours of the Snakes from depth maps obtained using a multi-resolution recursive shortest spanning tree (RSST) algorithm (Rodríguez- Rieiro, 2011). The algorithm, once the *z position* of the object of interest is known, returns a three-color image:

- Blank: If the analysis objective corresponds to a depth different from the depth of the survey.
- Gray: When the analysis objective is close to the depth of investigation.
- Black: When the content being analyzed corresponds to the depth of the investigation.

The initial contour is formed by the points that belong to the edge and are closest to the boundary between the gray and white parts of the previous image (Rodríguez- Rieiro, 2011).

Vese algorithm

The Chan- Vese method has been very useful to achieve the segmentation of objects or different anatomical structures in images with a large amount of noise or where the edges of the objects of interest are not defined. There are works in the literature that divide anatomical structures into groups (for example, the small intestine and blood vessels), as well as into industrial areas to produce carburetors, tires and other automobile parts. In general, the Chan- Vese algorithm is a segmentation method that aims to minimize the energy function (Hernández- Juárez *et al.*, 2017).

Experimentation

To measure the effectiveness of the selected algorithms, a series of tests were carried out. agreement with the guy of algorithm, which they executed with he following atmosphere of development: a computer that had an Intel Core i5 7200U at 2.5 Ghz processor and 8 GB of memory RAM on a 64-bit Windows 10 operating system; As for the images, the image 1 (main) was 5184 x 2912 pixels and 2.1 MB (figure 1), and image 2 was 336 x 408 pixels and 25.1 kB (figure 2); it above was processed using the Python programming language (version 3. 6. 6) and the package OpenCV (version 3.4.2).

Figure 1. Image 1 (main) 5184 x 2912 pixels

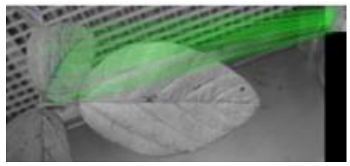
Source: self made

Figure 2. Image 2 of 336 x 408 pixels

Source: self made

For the implementation of the algorithm SIFT the results HE they can notice in figure 3, where 1377 and 263 descriptors were obtained for each image respectively (figures 1 and 2). These were processed in a time of 8782.877 milliseconds, with a RAM memory consumption of 46.16 MB (figure 3).

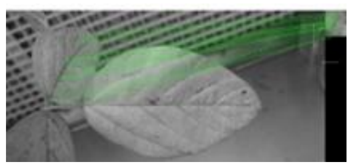
Figure 3. SIFT algorithm result



Source: self made

In how much to the algorithm SURF, 2553 were achieved and 153descriptors for each image respectively (figure 1 and 2), with a time of 7004.71 milliseconds and a RAM memory consumption of 65.75 MB (figure 4).

Figure 4. SURF algorithm result



Source: self made

As for the Harris algorithm, 46 corners were detected in a time of 3837.095 milliseconds, with a consumption of RAM memoryof 276,894 MB.

Figure 5. Harris algorithm result

Source: self made

Regarding the Shi-Tomasi algorithm, they stood out 1000 corners in a time of 3688,562 milliseconds with a consumption of memory of 104,417 MB.

Figure 6. Shi-Tomasi Algorithm Result

Source: self made

Relative to the active contour algorithms, Snake returned a time of execution of 40 seconds and a consumption of memory of 394,199 MB (figure 7).

Figure 7. Snake algorithm result

Source: self made

Regarding the Chan- Vese algorithm, there was an execution time of 7.7 minutes and a consume of memory of 1890.929 MB.

Figure 8. Chan-Vese algorithm result

Source: self made

Results

The board _ 1 summarizes the results reached with the algorithms SIFT and SURF.

Table 1. Results of the algorithms SIFT and SURF

DESCRIPTORS				
Algorithm	Fig. 1	Fig. 2	Time in more	Memory consumption
SIFT	1377	263	8782.877	46.16
SURF	2553	153	7004.71	65.75

Source: self made

Table 2 shows the results obtained with the Harris and Shi-Tomasi algorithms.

Table 2. Results of the algorithms Harris and Shi-Tomasi

PROSECUTION			
Algorithm	No. _ From Corners	Time in Ms.	Memory consumption
Harris	46	3837.095	276,894
Shi-Tomasi	1000	3688,562	104,417

Source: self made

Table 3 reflects the results obtained in the Snake and Chav-Vesse algorithms.

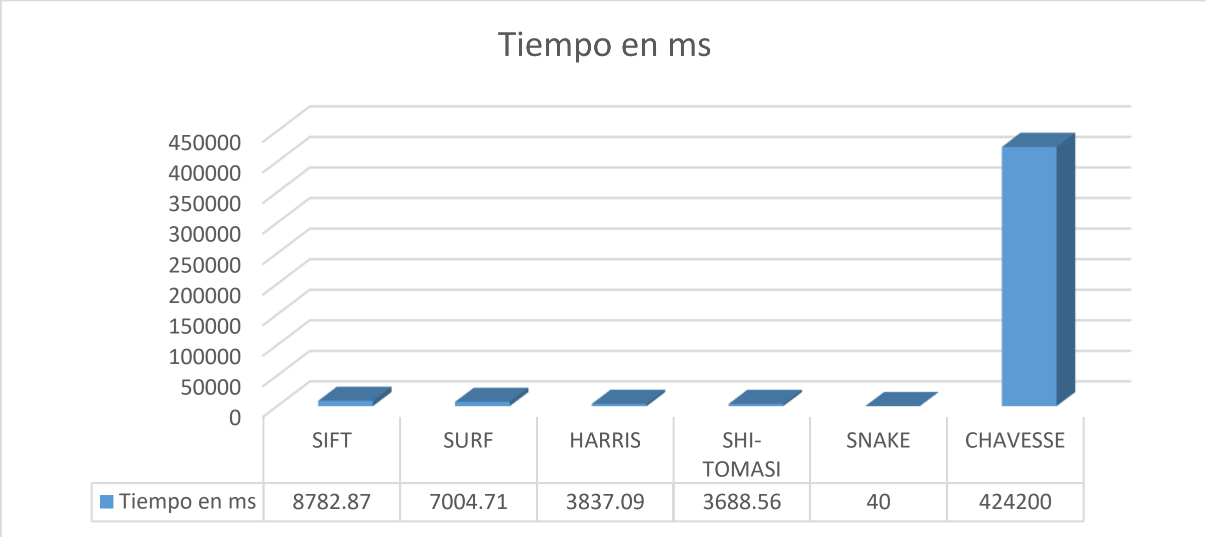
Table 3. Results of the Snake and Chav-Vesse algorithms

Algorithm	More time	Memory consumption
Snake	40	394,199
Chan- Vese	424200	1890.929

Source: self made

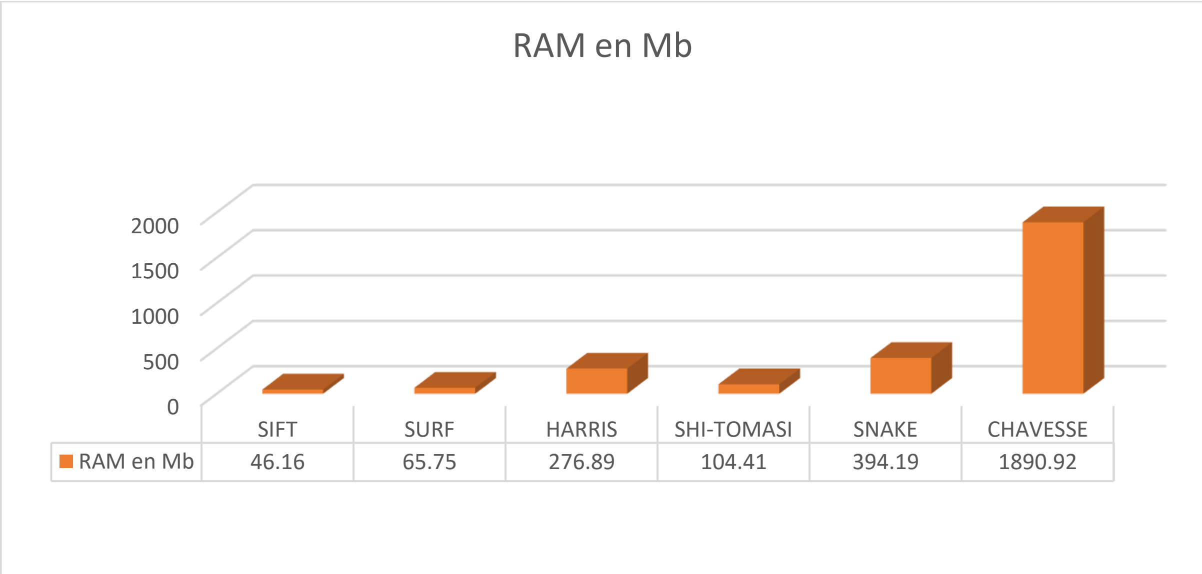
Figures 9 and 10 show the computational cost in terms of processing time consumption in milliseconds (figure 9) and memory consumption in MB (figure 10) to obtain the results of the analyzed algorithms.

Figure 9. Processing time consumption in milliseconds



Source: self made

Figure 10. Memory consumption in MB



Source: self made

Discussion

In a similar article by Ahmad *et al.*, (2021) that addresses the procedure to classify and detect soybeans, the execution time of said activity is calculated, and it can be observed that these times are slightly longer than those presented in the present study.

Likewise, in another study carried out by Razfar *et al.*, (2022), a soybean recognition method is proposed, for which both the RAM memory consumption and the time necessary to carry out these tasks are measured. In summary, times like those presented in this research are evident, although memory use is notably higher.

As has been observed during the experimentation, there are various algorithms that provide different characteristics of the images depending on the needs. In this sense, all of them have advantages and disadvantages depending on the results that are sought to be highlighted.

This research work aimed to present some of those algorithms available for image recognition, so it can be indicated that choosing one or the other will depend on the specific needs and the context where they are applied.

Finally, about computational cost, according to the results obtained in terms of time and RAM memory consumption, the most outstanding algorithm in both aspects was the Shi-Tomasi, hence it could be the best choice for recognition. of soybean leaves.

Conclusions

In the present work, the use of different types of algorithms for the recognition of soybean leaves was explained. This was achieved after an exhaustive investigation of the state of the art with the aim of testing only those algorithms recognized and recommended by scientific literature.

In this sense, it should be noted that these algorithms were analyzed, programmed, and tested with different images to measure their computational cost, which yielded disparate results. Even so, it can be noted that the Shi-Tomasi algorithm It can be chosen to recognize soybean leaves, since it presents an acceptable computational cost for the task assigned.

Future lines of research

As lines of research, more image recognition algorithms could be added and tested, as well as other computational techniques for detecting soybean leaves. Likewise, the algorithms that present the best extrapolating performance can be tested to recognize not only soybean leaves, but other types of plants (e.g., corn, beans, etc.).

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