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Capture and labeling image system for agriculture applications

Sistema de captura y etiquetado de imágenes para aplicaciones de agricultura

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Abstract

Artificial Intelligence methodologies and their learning has been used lately in the creation of image classification system. Such a system requires a training process that requires information, i.e. labeled images. This article presents a capturing and labeling image system for the creation and recognition base focus on agriculture. A case study of tomato jitomate (Lycopersicon esculentum) plants is analyzed to demonstrate the operation of the system and the methodology for capturing images. The system consists of a microcomputer raspberry pi 3, a video camera with pan-tilt-zoom control and a direction-adjustable lamp for capturing images. Besides, it also needs a graphical interface to select and label the regions of interest, this generates a file training that contains the knowledge base of interest. This contribution lies in the implementation of a system that accelerates the process of labeling and capturing images for agricultural applications.

Agriculture, Image capture, Learning

Resumen

El aprendizaje automático es una de las metodologías de la inteligencia artificial que se ha usado exitosamente en la creación de sistemas de clasificación de imágenes. Tales sistemas ocupan un proceso de entrenamiento que requiere información, por ejemplo imágenes clasificadas. En particular, los sistemas basados en entrenamiento supervisado requieren de imágenes o regiones etiquetadas en categorías. En este trabajo se presenta un sistema de captura e etiquetado de imágenes para la creación de una base de conocimiento enfocado a la agricultura. Un caso de estudio de plantas de jitomate (Lycopersicon esculentum) es analizado para demostrar el funcionamiento del sistema y la metodología para la captura de imágenes. El sistema consta de una microcomputadora raspbery pi 3 una cámara de video con control pan-tilt-zoom y una lámpara ajustable en dirección para la captura de imágenes. También, se usa una interfaz gráfica para seleccionar y etiquetar las regiones de interés, que genera un archivo que contiene la base de conocimiento de interés. Nuestra contribución radica en la implementación de un sistema que agilice el proceso de etiquetado y captura de imágenes para aplicaciones agrícolas.

Agricultura, captura de imágenes, aprendizaje

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Introduction

Image classification has always been a major challenge for the computer vision community. The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2010, consisted of classifying 1.2 million high-resolution images into 1000 different classes. The scientific community paid attention to the proposal based on convolutional neural networks with 60 million parameters, 650 000 neurons and 5 convolutional layers in the different tests reached places 1 and 5, (Krizhevsky et al., 2012).

In the challenges it is important to define the framework where image types are described, evaluation metrics, categories and ILSVRC tests are presented, (Russakovsky et al., 2015). In this sense, the task of categorising images requires a lot of human resources, so the development of tools that allow their labelling is of great importance.

There are several reference knowledge bases for image classification. Google has a knowledge base with 50 million images with 345 categories, the images contain hand-drawn pictures (scribbles) that represent something (Guo et al., 2018). WordNet is for example a lexicographic knowledge base where relationships between words in more than 200 languages are recorded, (Miller, 1995). Also, neural networks have been used to track people from a drone, (García-García, 2022). Convolutional neural networks have been applied to issue alerts for image recognition, (Jerez et al, 2022).

One requirement of automatic classification systems is that they deal with large amounts of information that must be organised and labelled when supervised learning is used. Currently, systems with higher classification rates make use of artificial intelligence where deep learning has gained wide acceptance. Deep learning is a multi-layer neural network learning that demands a large amount of data, (Alzubaidi, et. al. 2021). The traditional machine learning scheme follows the following workflow: image capture, pre-processing application (adjusting scale, colour, rotation, etc.), feature extraction (colour, texture, point of interest, geometric structures, etc.), selection of the most discriminative features and finally classification.

In contrast, machine learning-based systems have a three-stage system: image capture, deep learning model and classification.

Precision agriculture is a strategy that collects, processes and analyses spatio-temporal individual data and combines it with other sources of information for better decision-making to improve the quality, efficiency, profitability and sustainability of agricultural processes. To achieve this, precision agriculture uses data acquisition technologies and data processing systems (DeLay et al., 2022).

On the other hand, for the study of plant materials, the development phenology according to the BBCH scale for Solanaceae (Feller et al., 1995) is taken into account. According to this coding the main stages are: 0. Germination, 1. leaf development (main stem), 2. formation of lateral shoots, 3. longitudinal stem growth or rosette growth, shoot development (shoots) / tillering (main stem), 4. development of harvestable vegetative parts of the plant or vegetative organs of propagation / budding, 5. emergence of inflorescence (inflorescence). Emergence of inflorescence (main stem) / spiking, 6. Flowering, 7. Fruit development, 8. Colouring or ripening of fruit and seeds, 9.

In the seminal work of (Fisher R.A., 1936 & 1950) he presented a method of grading Irish flower varieties based on physical flower lengths for which a knowledge base called Irish dataset was created.

For the development of automatic image classification systems focused on agricultural applications such as counting leaves, fruits, flowers or detecting stages of development, it is of great importance to define the image capture process and its labelling, in order to obtain an adequate knowledge base for the training stage of our classifier.

In addition to classifiers, neural networks are applied to predict the fruit load for olive trees, (Asensio Jiménez et al., 2022).

A very important aspect for the creation of knowledge bases is the architecture (hardware and software) that facilitates the recording of information such as those used in Industry 4.0, (Lopez et al. 2022).

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This paper presents the implementation of a system that streamlines the process of tagging and capturing images for agricultural applications. The paper is organised as follows: first a discussion on phenological categorisation is presented, then a description of the image capture and labelling system is presented, then the structure of the knowledge base is presented, then the case study tomato plants (Lycopersicon esculentum) is presented. Then, the capture system is presented in a distributed format where two or more devices can be networked to capture and tag images. Finally, the results obtained and conclusions are presented.

Phenological categorization of plant development

The BBCH scale for Solanaceae (Feller et al., 1995) describes the developmental stage of plants. Table 1 shows the phenology of development for coding in developmental stages and their number of stages with their two- and three-digit description code.

Cod. 2 dig.	Cod. 3 dig.	Description
Principal growth stage: Germination 0		
0	0	Seed, dried
To:		
9	9	Emergence: cotyledons break through the soil surface
Principal growth stage 1: Development of leaves (main stem))		
10	100	Cotyledons, unfolded Emergence: cotyledons break through the soil surface completely
To:		
19	109	9 or more main stem leaves, unfolded
Principal growth stage 2: Fromation of side shoots		
21	201	1st apical primary side shoot visible
To:		
Principal growth stage 3: Stem elongation (main shoot)		
30	300	onset of stem elongation
To:		
39	309	Nine or more visible extended internodes
Principal growth stage 5: Inflorescence emergence		
51	501	1st visible inflorescence (1st erect bud)
To:		
59	519	19th visible inflorescence
Principal growth stage 6: Flowering		
61	601	1st inflorescence: 1st flower open
To:		
69	619	19th inflorescence: 1st flower open
Principal developmental stage 7: Fruit development		
71	701	1st fruit cluster: 1st fruit has reached its typical size
To:		
79	719	19th fruit cluster. The 1st fruit has reached its typical shape and size.
Principal growth stage 8: Ripening of fruits and seeds		
81	801	10% of the fruits reach their typical ripe colour.
To:		
89	807	70% of the fruits reach their typical ripe colour.
Principal Developmental Stage 9: Senescence		
97	907	dead plants

Table 1 BBCH scale for developmental stages in tomato
Source: (Feller et al., 1995)

This scale is a candidate for labelling plants at different stages of development. The stages of development will depend on the interest of the application, for example, if the germination stage is of interest, the detection of 00,01,03,04,07 and 09 are the moments to be categorised.

Another application can be the appearance of flower buds and fruits which can be the stages 5x, 6x, 7x and 8x respectively. Also, the moment when the plant dies can be of interest, in this case it is important to detect the 9x stage.

Image capture and labelling

In this work, the creation of an image-based knowledge base and its labelling is of major interest. However, in order to take images that can be useful in an image classification system, they must meet some characteristics, such as:

- Lighting. There must be the necessary amount of light for colours, shapes and textures to be seen.

- Light reflection. Care must be taken to ensure that the shots are not saturated with light. This produces images with a white appearance. It is important to direct the light so that this phenomenon does not occur.

- Focus and zoom. The images must be in focus, so the zoom plays an important role and must be adjusted so that the images are sharp.

Taking into account the points described above, for the implementation of the image capture system we used a lamp adjustable in position and orientation, a raspberry pi 3 microcomputer with raspbian operating system and a tilt-pan-zoom camera model Logitech PTZ Pro 2 USB HD 1080P, see Figure 1. We chose to use a raspberry instead of a PC because it has the computational resources for only the acquisition of images, and the choice of a PC would be a waste of resources. For the user to register the data to the knowledge base, a graphical interface was created to speed up the capture process.

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Therefore, for the implementation of the capture system, raspbian was used as the operating system, OpenCV and Python as the programming language. OpenCV is a library for computer vision that allows connecting digital image acquisition peripherals, such as 2D and 3D cameras.

Figure 1 Image capture system hardware: camera, lamp and raspberry pi 3

The user interface that allows capturing and labelling to be performed is shown in Figure 2, in addition to a small piece of Python code. This interface allows to configure the path where the images are saved and to select a variable size region of the image that represents some state of development.

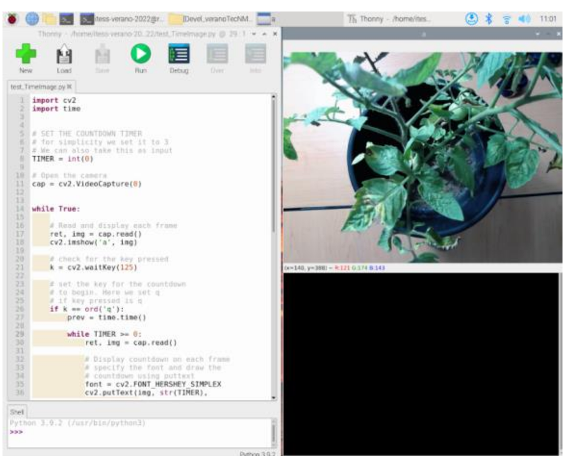

Figure 2 Image capture system hardware: camera. Lamp and raspberry pi 3

Image knowledge base

- The knowledge base is created by organising the images, registering the regions of interest and manually labelling them. The images are stored in a file structure as shown in Figure 3. In addition to the image capture, a record is created containing the following information:
- Plant i, i is the plant identifier.
- Day j, the jth day after the first capture.
- Image k, image k taken of plant i and day j.
- Region l, region l is composed of the coordinate of the upper left corner, as well as the width and the height.
- Region l label. The label represents the category to which region l corresponds..

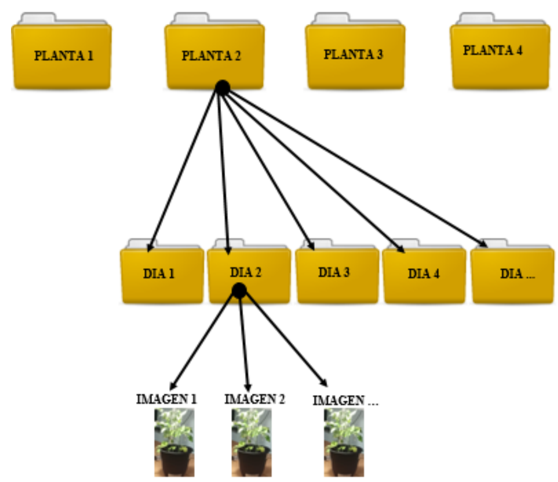

Figure 3 Suggested organisation of images.

The above labelling format allows an image to contain several regions of interest for the application. An example of a record in this format is shown in Table 2:

Plant	Day	Image	Region	Label
1	3	1	(0, 0, 50, 50)	leaf
1	3	1	(100,200, 80, 60)	stem
2	4	3	(200,200, 60, 60)	fruit
…	…	…	…	…
…	…	…	…	…

Table 2 Labelling registration form

The first and second rows represent plant1, day 3, image 1 and have two regions, one labelled leaf and one labelled stem. The third row represents plant2, day 4, image 2 and has one region labelled as fruit.

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For our system the records are saved in a cvs format, however, other file types such as json or xml can be used. Similarly a database manager can be created to concentrate the records, this would allow for example to work with several distributed capture systems. On the other hand, supervised learning systems require a knowledge base for their training stage, see Figure 4.

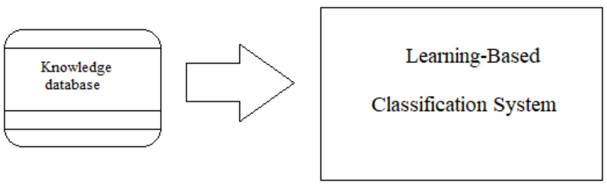

Figure 4 Diagram of a learning system

Case study for tomato (Lycopersicon esculentum) plants)

The steps in the procedure for creating a knowledge base are presented below:

1) Define the problem domain. The domain refers to the type of plant, plants, stage of development or diseases I want to classify. For our case study we define tomato (L. esculentum) plants.

2) Establish the categories of interest. Then the categories that I want to classify in the problem domain are established. For our case we will use the detection of the organs of tomato plants: main stem (stage 1), leaf (stage 2), flowers (main stage 6) and fruits (main stage 8).

3) Capture images using the capture and labelling system. In our case plant i is chosen, on day j, image k is captured and region l is selected and categorised.

For our case study, 5 tomato plants were chosen, records were made for 15 days, 5 images were taken per day and 8 regions (if there are 2 of each for the categories mentioned above). Figure 5 shows the image of the reference plants on day 0.

Figure 5 Images of the plants on day 0. In the top row from left to right plants 1, 2 and 3

During the image capture process, the regions of interest and their category are manually identified. For example, in Figure 5, stem and leaf are selected, the red and blue squares respectively.

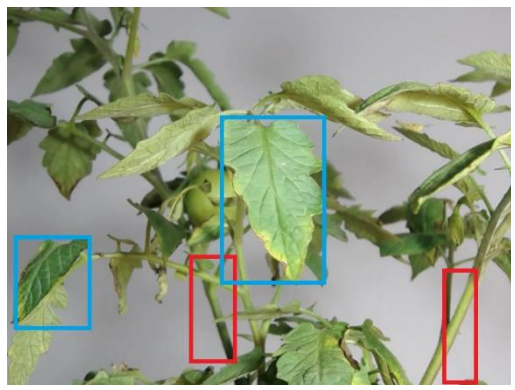

Figure 6 Image 1 of plant 1, day 0, stem and leaf regions.

One of the features to have when generating a knowledge base is to have a variety of information, e.g. you can zoom in and out, rotate the plant, and vary the camera pose. In addition to the plant's labels of interest, you can also define additional categories such as background or even undefined. As the plants continue to grow, Figure 7 shows their status on day 15. In picture 3, leaves in senescence state can be observed. Considering picture 5, it is possible to observe the development of the plant as the days go by and particularly, the growth of the fruits.

Figure 7 Pictures of the plants on day 15. In the top row from left to right plants 1, 2 and 3. And in the bottom row plants 4 and 5

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Distributed Capture System

The application of information and communication technologies plays a very important role in the development of the proposed system. Taking advantage of the ethernet or wifi connectivity capacity of the raspberry microcomputers. Several systems can be networked and information can be stored in a remote storage space. Such a configuration is shown in the diagram in Figure 8.

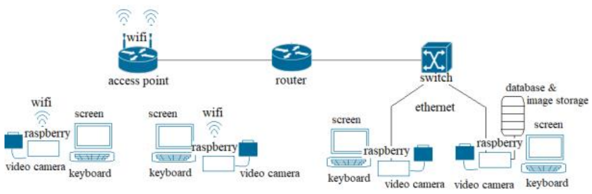

Figure 8 Distributed capture system. This system requires more infrastructure such as routers, switches and access points

This architecture allows images to be captured in different locations simultaneously, without the need to move the system. Attention must be paid to the lighting conditions and the quality of the cameras.

Results

A functional system for capturing and tagging images for the creation of a knowledge base was implemented. In addition, a distributed design is proposed that allows connecting several networked devices in order to make the capture of information more agile.

Also, a graphical user interface programmed in Python and using the OpenCV library was developed. To facilitate the capture and tagging of images, a file organisation structure and a format for tag registration were defined here.

The development of the system was applied in a case study where a knowledge base was created for tomato plants for the tags: stem, leaf, fruit, shoot, dead leaf, and background. Our knowledge base has 375 images and 3000 records.

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Conclusions

This paper presents the importance of having information capture systems and the creation of knowledge bases. The process of tagging and the difficulty that can be encountered when generating information manually was discussed. It is therefore important to integrate different technologies for the creation of systems such as microcomputers, operating systems, networks and image acquisition peripherals. It is important to define categories according to the problem domain.

When developing classifiers, little emphasis is placed on the generation of information and the infrastructure and human resources required to create it.

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