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STATISTICS

Deep learning in flower quantification of Catharanthus roseus (L.) G. Don

Carmélia Maia Silva[1*], Alcinei Místico Azevedo[2], Leonardo Amaral Mozelli[3], Elka Fabiana Aparecida Almeida[2] and Delacyr da Silva Brandão Júnior[2]

[1]Departamento de Agricultura, Universidade Federal de Lavras, Aquenta Sol, 37200-000, Lavras, Minas Gerais, Brazil. [2]Instituto de Ciências Agrárias, Universidade Federal de Minas Gerais, Montes Claros, Minas Gerais, Brazil. [3]Departamento de Engenharia Eletrônica, Universidade Federal de Minas Gerais, Belo Horizonte, Minas Gerais, Brazil. *Author for correspondence. E-mail: carmelia.silva@estudante.ufla.br

ABSTRACT. Deep learning techniques are increasingly automating tasks performed manually, thanks to the robustness and precision of their results, which encourages their use as a tool in the floriculture and landscaping sector. The amount of floristic species is wide and diverse, whether in shape, texture or color. The ornamental species *Catharanthus roseus,* considered to have a tropical climate, it has cultivars in which the color of the flowers is one of its attractive aspects, and these can vary from white to different shades of pink. Thus, the objective of this work was to use deep learning techniques to evaluate the potential of the two-stage convolutional approach called Mask R-CNN to quantify C. roseus flowers and qualify them in terms of color for application in the floriculture and landscaping sectors. 700 images were collected in gardens in the North of Minas through smartphone cameras, of which 500 had both pink and white flowering and 200 had only the leaves, to compose the *background*. For the composition of the synthetic image bank, 100 white flowers and 100 pink flowers were processed in png format and formed the foreground, the two being separated as two subclasses. The training using the transfer learning technique with the Mask R-CNN algorithm was carried out in Google collaborative, with commands in python language and libraries from the Github platform. Through rating quality evaluators, the Convolutional Neural Network Mask R-CNN showed overall accuracy above 90% and accuracy above 80%. The network proved to be efficient in estimating the number of flowers, in addition to detecting and segmenting them, qualifying them in terms of color. Therefore, the methodology can be used in the floriculture and landscaping sector to estimate and quantify flowers through images.

Keywords: Image analysis; floriculture; landscaping; mask R-CNN; convolutional neural networks.

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Introduction

Catharanthus roseus (L.) G. Don is a medicinal and ornamental plant popularly known as vinca, good night, vinca de Madagascar, periwinkle and maria without shame (Nejat et al., 2015). The species is a dicot of the botanical family of Apocynaceae, which comprises several species such as: desert rose (*Adenium obesum)*, alamanda (*Allamanda cathartica)* and the oleander (*Nerium oleander)* (Colombo et al., 2015; Santos et al., 2022). Native to the island of Madagascar on the African continent, *Catharanthus* it is a perennial, subshrub plant, which can reach one meter in length (Lahare et al., 2020).

According to Lahare et al. (2020), the most common cultivars of *C. roseus* are those with pink flowers called "Rósea", where they differ between dark pink and light pink. The other cultivar is the one with white flowers, being called "Alba". Despite these two differences, variegated pink and white flowers are still found. The flowers are usually solitary or twinned, axillary with five petals and have a hypocrateriform corolla (Lorenzi & Matos, 2008). The fruits are composed of two dehiscent follicles, the seeds are small, black in color and in large numbers, the pod can reach up to three centimeters in length and when dry, it opens and the seeds are dispersed by the wind (Lorenzi & Matos, 2008).

C. roseus is widely cultivated in countries on the African continent, India, Australia and some countries in the European region (Lahare et al., 2020). The species has spread through several regions with a tropical climate, in Brazil it is used mainly in landscaping, and its occurrence occurs spontaneously in several places such as squares, gardens, sidewalks and also in a cultivated way, as its flowers are a great attraction for flowerbed compositions in full sun (Lorenzi & Matos, 2008).

For landscaping projects, there is a demand for the construction of flowery, functional and beautiful gardens, which makes the sector resort to increasingly advanced technologies. We can mention among the technologies as an example, the creation of applications that facilitate the management of the landscaper in the identification of species by the organs of the plant, such as its flowers (Wäldchen et al., 2018). In this context, the Computer Vision, an area of study of computing dedicated to extracting information from digital images, has facilitated the performance of these tasks efficiently and accurately, and such techniques can help landscaping programs such as Sketchup, Photolandscape, among others. Technologies based on Computer Vision can also be applied in horticulture sectors, such as in the identification and quantification of flowers for pharmacological purposes, as in the case of C. roseus which, in addition to being an ornamental, is also a medicinal plant.

Many works contemplate the use of images for different processes of handling flowers, among which we can mention: segmentation of images of apple blossoms Tian et al. (2020), real-time detection of flowers of different types of apple trees Wu et al. (2020) and detection and classification of the area of disease lesions in seedlings of the Phalaenopsis orchid, using image processing (Huang, 2007).

The Convolutional Neural Network - CNN, are a special model of deep learning neural networks, inspired by the functioning of the cerebral cortex of living beings during the image classification task, where the hierarchical architecture of a structure that presents a simple perception can work in a complex way (Hubel & Wiesel, 1968).

The state-of-the-art approaches to image instance segmentation are based on object detection using CNNs and are categorized into two classes: one-stage detectors and two-stage detectors (Liu et al., 2019). In two-stage detectors, one step proposes candidate regions of interest (ROIs), which are refined and delimited in a later step, completing the identification.

The Mask R-CNN approach is one of the most prominent representatives among two-stage detectors. In several researches, it is evident how efficient it is in the resolution and recognition of different objects in images (Liu et al., 2017). It has aided in the phenotyping of plants Toda et al. (2020), plant counting and sizing Machefer et al. (2020) among other works that describe it as one of the networks that present high values regarding the precision.

The identification, detection and segmentation of objects in the images are carried out through training, where the images are demarcated with bounding boxes on the objects of interest, distinguishing them in terms of the determined class (Johnson et al., 2021).

Thus, the objective was to evaluate the potential of the Mask R-CNN network in the floriculture and landscaping sectors to quantify *Catharanthus roseus* (L.) G. Don flowers and qualify them in terms of color through images.

Material and methods

A set of images of the Catharanthus roseus species was used, obtained through the cameras of two smartphones: (Sony Xperia XA1 Plus, model G3426; Aperture: f/2; Exposure time: 1/30s; Flash: off, Focal length: 4.22mm; ISO value: 50, resolution: 5520x4140 pixels and from Redmi Note 9, Xiaomi: Aperture: f/1.79; Exposure time: 1/60s; Flash: off; Focal length: 4.74mm; ISO value: 228; resolution 8000x6000 *pixels*).

The 700 images were collected in gardens in the North of Minas Gerais - Brazil, in the city of Montes Claros and Coração de Jesus, the images were obtained on different days, between March and October 2021, between 7 am and 4 pm. The photos were obtained from plants over 4 months old measuring 35 to 100 centimeters in height. Of these images, 500 have flowers, 384 with pink flowers, ranging from medium to dark tones, 100 images with white flowers and 16 containing white and pink flowers. And 200 images do not have flowers, containing only leaves of the species, being used as background.

A synthetic image bank was created. For this, images were created in png format (with transparent background) containing only the flower, totaling 100 white vinca flowers and 100 pink flowers (Figure 1). In the creation of the synthetic bench, these images in png format composed the foreground with two subclasses (white vinca and pink vinca), vinca is the popular name of Catharanthus roseus, however the word vinca was left for the classes. The editing to obtain these png images was done with the help of the GIMP software version 2.10.22. As for the background, 200 images were considered without the presence of flowers and with a background composed only of leaves of the species.

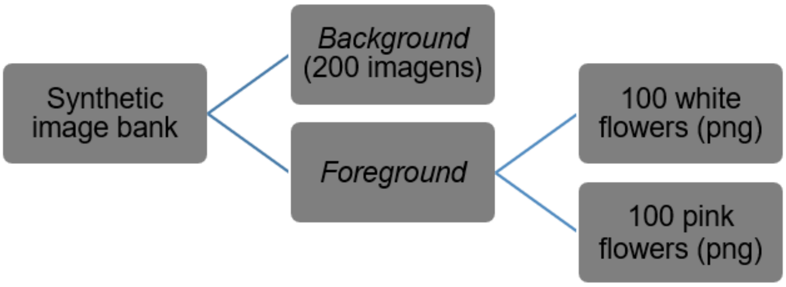

Figure 1. Synthetic image bank for training.
Source: the author.

The synthetic image bank was created in COCO format with the help of the cocosynth library (https://github.com/akTwelve/cocosynth) in the Google collaborative environment using the python programming language. For this, the number of 3000 images for training and 1000 images for validation was established. Within the algorithm used, the maximum number of five png objects per image was randomly established. The positioning of these png images on the background was done randomly. In addition, for the creation of the synthetic image bank, random changes in rotation, scale and brightness were allowed for the superposition of png images on the background (Figure 2a). Through this methodology, the image mask (Figure 2b) and the file with the instance definitions in json format were obtained automatically. The size of the output images has been set to 320x320 pixels.

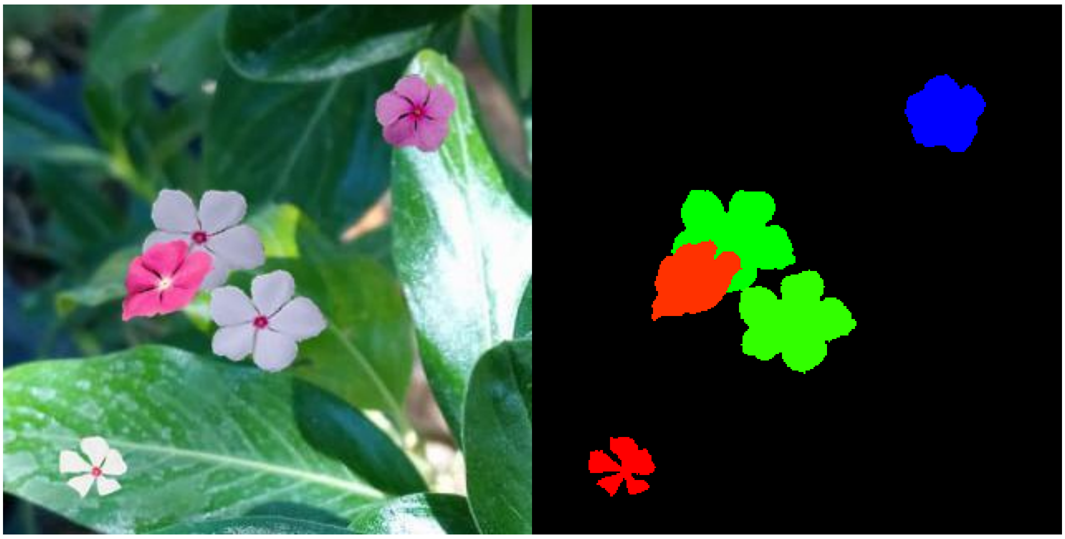

Figure 2. Example of synthetic database images with png images on the background (a) and its respective mask (b) obtained by the cocosynth library.
Source: the author.

To train the CNNs, the Mask R-CNN algorithm was used (https://github.com/matterport/Mask_RCNN), this step was also performed in Google collaborative, the execution environment defined was the GPU making the training faster. The network used to extract the characteristics was ResNet101 and the pre-trained model MS COCO. When using the Mask R-CNN algorithm, we considered the use of 5 images per GPU, 3 classes (background, pink flowers and white flowers). In (Table 1) the information of the other configured parameters is summarized.

The Transfer learning technique was used, which starts the training from synaptic weights already trained in cocodata format. 100 training epochs were considered for the adjustment of the synaptic weights of the last layers of the network and another 100 epochs for the adjustment of the synaptic weights of all the layers of the network.

At the end of the network training, the test with the images was performed. At this point, a minimum confidence of 90% was established for the identification and classification of flowers. To evaluate the accuracy in detecting objects by Mask R-CNN, a contingency table was built, resulting from the classification prediction compared with the real classes.

Table 1. Arbitrated parameters for the adjustment of Mask-RCNN type networks.

Parameters	Values
BACKBONE	resnet101
BACKBONE_STRIDES	[4, 8, 16, 32, 64]
BATCH_SIZE	10
BBOX_STD_DEV	[0.1 0.1 0.2 0.2]
COMPUTE_BACKBONE_SHAPE	None
DETECTION_MAX_INSTANCES	100
DETECTION_MIN_CONFIDENCE	0.7
DETECTION_NMS_THRESHOLD	0.3
FPN_CLASSIF_FC_LAYERS_SIZE	1024
GPU_COUNT	2
GRADIENT_CLIP_NORM	5
IMAGES_PER_GPU	5
IMAGE_CHANNEL_COUNT	3
IMAGE_MAX_DIM	320
IMAGE_META_SIZE	15
IMAGE_MIN_DIM	320
IMAGE_MIN_SCALE	0
IMAGE_RESIZE_MODE	Square
IMAGE_SHAPE	[320 320 3]
LEARNING_MOMENTUM	0.9
LEARNING_RATE	0.001
MASK_POOL_SIZE	14
MASK_SHAPE	[28, 28]
MAX_GT_INSTANCES	50
MEAN_PIXEL	[123.7 116.8 103.9]
MINI_MASK_SHAPE	(56, 56)
NAME	Vinca
NUM_CLASSES	3
POOL_SIZE	7
POST_NMS_ROIS_INFERENCE	500
POST_NMS_ROIS_TRAINING	1000
PRE_NMS_LIMIT	6000
ROI_POSITIVE_RATIO	0.33
RPN_ANCHOR_RATIOS	[0.5, 1, 2]
RPN_ANCHOR_SCALES	(8, 16, 32, 64, 128)
RPN_ANCHOR_STRIDE	1
RPN_BBOX_STD_DEV	[0.1 0.1 0.2 0.2]
RPN_NMS_THRESHOLD	0.7
RPN_TRAIN_ANCHORS_PER_IMAGE	256
STEPS_PER_EPOCH	50
TOP_DOWN_PYRAMID_SIZE	256
TRAIN_BN	False
TRAIN_ROIS_PER_IMAGE	32
USE_MINI_MASK	True
USE_RPN_ROIS	True
VALIDATION_STEPS	5
WEIGHT_DECAY	0.0001

Source: The author.

The following evaluators were used to verify the efficiency of the network in detecting objects:

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

$$F-1 = \frac{2*Precision*Recall}{Precision+Recall} \tag{2}$$

$$F-1 = \frac{2*Precision*Recall}{Precision+Recall} \tag{3}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

$$Specificity = \frac{TN}{TN+FP} \quad (5)$$

Where: In the TP equations referring to true positives, FN to false negatives, FP to false positives and TN to true negatives.

Results and discussion

The loss functions for mrcnn_mask_loss, mrcnn_bbox_loss and mrcnn_class_loss are shown in (Figure 3). By observing the loss function over the iteration epochs, from epoch 22 onwards, stabilization in the quality of fit was obtained. However, after the hundredth epoch, when training only the last layer of the network was stopped and training of all layers began, there was a small improvement in the adjustment, with subsequent stabilization.

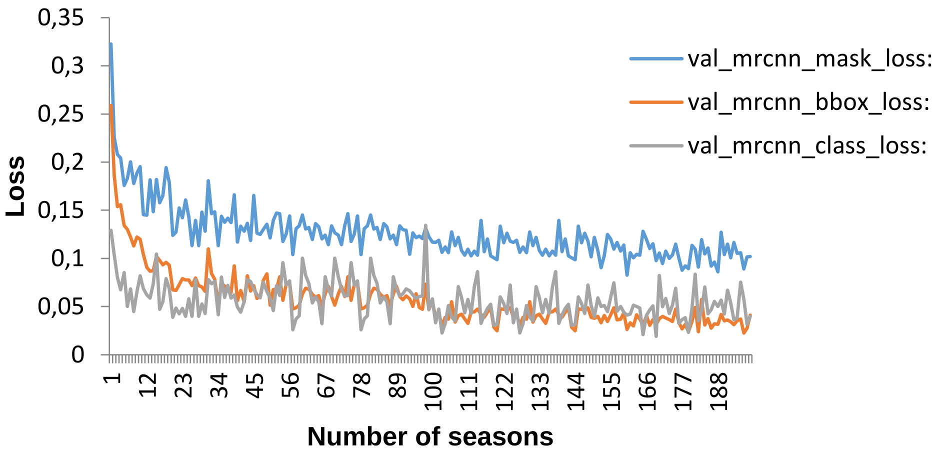

Figure 3. Iteration loss function curves in the classification of flowers of *Catharanthus roseus* (L.) G. Don.
Source: The author.

By training the epochs with the Mask R-CNN algorithm, the segmented images of the data set used for the test are obtained, established with a confidence value of 90%. In (Figure 4) an image can be seen as an example before the inference and after with the bounding box and the segmentation mask on the detected and identified object.

Figure 4. Detection and identification of the vinca flower by the bounding box and segmentation mask.
Source: The author.

The contingency table or confusion matrix (Table 2) for the two analyzed subclasses showed 1719 pink and 443 white flowers, considered to be true positives. For the false positives within the images, 51 objects were classified as pink flowers and 47 as white flowers, these false positives are when the network classifies the object incorrectly. False negatives occurred when there were both pink and white flowers in the images and the network was unable to classify them.

To verify the efficiency of the studied network, precision, recall, F-1, accuracy and specificity were estimated (Table 3). For the two subclasses analyzed, greater precision was obtained for the pink vinca, with a precision value of 97% and for the white vinca the value was 83%, precision refers to the number of hits of the positive class, indicating how much the result can be truly correct.

Table 2. Contingency table.

Class	Reality	Classification by network	
		Sim	Não
White crease	Yes	TP = 443	FN = 90
	No	FP = 47	TN = 157
Pink crease	Yes	TP = 1719	FN = 46
	No	FP = 51	TN= 157
Crease (White + Pink)	Yes	TP = 2162	FN = 136
	No	FP = 98	TN = 314

Source: The author.

Table 3. Values referring to precision, recall, F-1, accuracy and specificity evaluated in the classification of pink and white vinca flowers.

Classes	Precision	Recall	F-1	Accuracy	Specificity
Pink crease	97%	97%	97%	95%	77%
White crease	83%	90%	86%	81%	64%
Crease (White + Pink)	96%	94%	95%	91%	76%

Source: The author.

For the evaluation of recall and F-1, the values for the pink vinca were 97% in both, these same evaluations for the white vinca presented the value of 90% for recall and 86% for the F-1. The recall refers to the chances of the network correctly detecting the object of interest and the F-1 is the harmonic mean of the precision and recall metrics. In this study, both precision and recall showed high values and this harmonic mean remained with the values of 97 and 86%.

As for the results regarding the accuracy, it was possible to verify that, for the pink vinca, the result was superior to that of the white vinca, obtaining a higher quality in the classification, with an accuracy of 95 and 81%. This lower value obtained for the accuracy of the white vinca subclass may have occurred because the images showed a greater amount of pink flowers, which ended up influencing the values used for the equation.

The specificity evaluation metric refers to the ability of the network not to classify other objects within the image that are not pink flowers or white flowers. The percentage obtained for this metric was 77% for pink vinca and 64% for white vinca.

The values obtained for the metrics in relation to the two subclasses white vinca plus pink vinca, it can be observed that for the precision, recall, F-1 and accuracy in the classification of this total dataset, the values were above 90%. This demonstrates that the network was able to efficiently identify the vinca flowers in the two colors in the images.

In Figure 5 (a) and (b) it is possible to observe how the network was efficient in estimating the number of flowers in the set of images. In Figure 5a, the estimated number of vinca flowers in both colors is presented. 5b, it is possible to observe the accuracy of the network in estimating the flowers, regardless of the color.

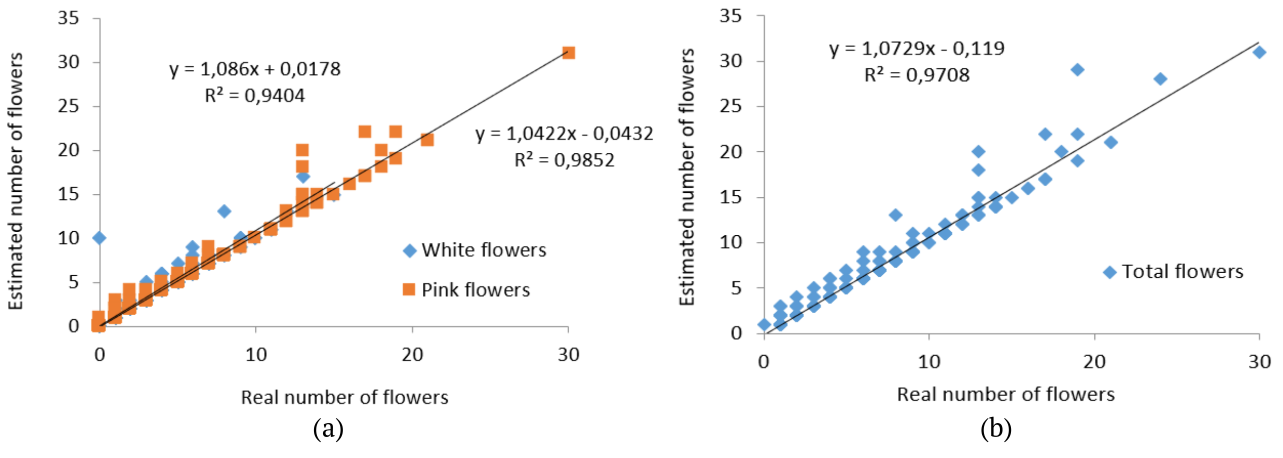

Figure 5. Estimate of the number of pink and white flowers (a) and the number of total flowers (b) in each photo.
Source: The author.

The Convolutional Neural Network used was efficient in estimating the number of flowers separated by subclasses, being white and pink flowers, as well as efficient in estimating the total number of flowers regardless of color. This shows that the application of the network to landscape projects can work as an efficient and accurate tool for determining the number of flowers, either by color, or just estimating the total number.

The Mask R-CNN algorithm is a methodology that presents high precision in image detection and segmentation (Zhang et al., 2019). The Convolutional Neural Networks, when used in image analysis, manage to extract features from a respective object within the studied image from a network training (Khan et al., 2020).

The loss rates during the iterations demonstrate the efficiency of networks in adjusting to enable the detection of flowers (Figure 3), as there was a reduction in their estimates, for: The *"mrcnn_mask_loss",* which is equivalent to the masks created in the identification of objects; The *"mrcnn_bbox_loss"* referring to the loss attributed in the location of a bounding box in class identification; and the *"mrcnn_class_loss"* which is associated with loss attributed to the improper classification of objects that are in the proposed region (*region proposal*) (Bakr, 2021).

The smaller the values presented by the loss functions in the iteration, the greater the chances of the predictions coming out correctly as in the real images (Tian et al., 2020). In addition, there was stabilization of the curves of these loss functions, indicating that increasing the number of iterations would not improve the quality of the fit.

For quality evaluators in the classification by the Convolutional Neural Network, in this work carried out for the detection of flowers with the use of Convolutional Neural Networks, the precision presented good results, with an estimate of up to 97%, which proves the efficiency of the network for the detection of flowers, even when there are more than two classes, and the flowers have different shapes and colors (Table 3).

In a dataset composed of apple blossoms trained with Convolutional Neural Networks, using only 100 test images and the same extractor network ResNet101 used in our work, Tian et al. (2020), managed to obtain, in addition to an average accuracy of 95.90%, a recall rate of around 95.37% and an F-1 of 95.90%. According to the authors, these rates surpass other works carried out previously with the purpose of segmenting flowers in images.

According to Tan et al. (2016) and Hiary et al. (2018), the larger the data set, that is, the greater the number of images within the set, the better the classification, robustness and precision of the methodology used. Hiary et al. (2018), when using Convolutional Neural Networks to classify a range of flowers, of different types and formats in three data sets, their segmentation and flower detection results presented a percentage of 80% for the correct classification of images over all images of the sets. According to the authors, it was possible to obtain 97% for classification of these same sets, where only 168 images out of a total of 10,000 were classified incorrectly.

The use of deep learning methodologies were also used by Wu et al. (2020) for fast and accurate detection of apple blossoms, the neural networks used were able to make fast and accurate detections, even taking into account that the apple blossom has a reduced size and the images were with different illuminations. The process mainly helps to predict the yield of the orchard, in addition, the value for precision was 97.31%.

For image processing using Deep Learning methods, the greater the amount of data, the better the training samples will be and thus it is possible to obtain the maximum performance of the network and model that will be used for segmentation, detection and identification of objects in images (Tan et al., 2016).

However, although the amount of images used by Tian et al. (2020) and in the present work was reduced, there was good efficiency in training the networks. This can be explained by the training using the creation of the synthetic image bank. The creation of a synthetic database of images allows improvements in the performance of the network and in the results regarding the segmentation (Sobhaninia et al., 2019).

Different techniques using Computer Vision have been used in activities to assist in tasks performed by the floriculture and landscape sector. The creation of applications that mainly help in the identification and recognition of species, they use Computer Vision as a strategy to create a varied bank of plant images and become didactic tools that help in the teaching-learning process in the construction of landscape projects, substantially for inexperienced landscapers or even for laymen (Wäldchen & Mäder, 2018; Wäldchen et al., 2018).

Flower identification processes present themselves as complex tasks, and the automation of these processes that involve identification can contribute and benefit several professionals and sectors.

For the identification of the flowers of *Catharanthus roseus* (L.) G. Don, the training using the Mask R-CNN Convolutional Neural Network showed good accuracy, which makes the network possible as an allied tool for flowering seedlings producers and landscapers, and can be used to detect flowers in different stages of development, identify flowers in terms of color and quantify them from images.

Conclusion

The Mask R-CNN model was efficient in estimating the number of flowers, detecting and segmenting the flowers in terms of color. Therefore, the methodology used is a useful tool to be used in the floriculture and landscaping sectors through the quantification and qualification of flowers from images.

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