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Development of an algorithm for ladybird beetle detection in nature

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RESUMEN

La cantidad de especies de mariquitas, así como su interacción con los ecosistemas debido a su introducción como controladores de plagas, hacen necesario el desarrollo de una herramienta que permita su rápida y eficiente detección y estudio en la naturaleza. Dado que las especies introducidas pueden volverse invasoras, superar a las mariquitas nativas y perturbar los ecosistemas locales, además la sobrepoblación de mariquitas puede causar daños a los cultivos y tener un impacto negativo en los terrenos agrícolas. Debido a esto, proponemos un modelo de dos pasos para detectar y segmentar este tipo de insectos. En el primer paso, usamos un modelo de detección llamado YOLOv8, que genera bounding boxes con mariquitas en la imagen de entrada. Luego, en el segundo paso, usamos un modelo de segmentación basado en el contorno activo tradicional, llamado contorno activo "Snake", que toma los cuadros delimitadores y segmenta los insectos mariquita presentados dentro de ellos. El modelo propuesto fue validado en una base de datos pública obtenida del proyecto iNaturalist. Los mejores resultados de las métricas de DICE e IoU (Interacción sobre Unión) de 84,82% y 73,73% se obtuvieron con 300 épocas y un umbral de detección de precisión de 0,75 en el método YOLOv8, 300 puntos en la inicialización de contorno activo "Snakes", 0,01 como valor alfa y 100 iteraciones. Por lo tanto, la combinación del detector Yolov8 y el modelo de contorno activo "Snakes" nos permite crear un método de detección que ayuda a segmentar las mariquitas con mayor precisión.

ABSTRACT

The number of species of ladybird beetles, as well as their interaction with ecosystems due to their introduction as pest controllers, make it necessary to develop a tool that allows quick and efficient detection and study in nature. Since, introduced species can become invasive, outcompete native ladybirds and disrupt local ecosystems, also over population of ladybirds can cause damage to crops and have negative impact on agricultural yields. Due to this, we propose a two-step model for detecting and segmenting these types of insects. In the first step, we used a detection model called YOLOv8, which generates bounding boxes with ladybird beetles in the input image. Then, in the second step, we use a segmentation model based on the traditional active contour, named "Snakes" active contour, which takes the bounding boxes and segments the presented ladybird beetle inside them. The proposed model was validated in a public database obtained from the iNaturalist project. The best results of the DICE and interception over union metric scores of 84.82% and 73.73% were obtained with 300 epochs and an accuracy detection threshold of 0.75 in the YOLOv8 method, 300 points in the "Snakes" active contour initialization, 0.01 as an alpha value and 100 iterations. Therefore, combining the Yolov8 detector and "Snakes" active contour model allows us to create a detection method that helps to segment ladybird beetles more accurately.

Key words: Deep Learning, YOLO, Active Contour, detection, segmentation, ladybugs.

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1. INTRODUCTION

The Coccinellidae, more known as ladybird beetles, is one of the most commonly known family of beetles due to its appearance. There are around 6000 known species of ladybirds in the world (Carvajal, 2016), although, every year, new species are discovered in different countries, such as Ecuador. Due to the variety of species of this insect, there is just a little information about their geographic distribution (González and Větrovec, 2021) and their displacement due to the introduction of invasive species. In the 80s, some species of ladybirds were introduced in several countries since these insects can feed on aphids, mites, and larvae, which is why they are considered natural pest controllers (Carvajal, 2016), (Majerus, 2009), (Belyakova and Polikarpova, 2020). Normally, ladybirds are used to control aphids that are harmful to crops. However, due to this activity, they also cause the reduction of the population of endemic species of aphids that are not harmful to crops and other species of ladybirds. In addition, they are carriers of pathogens and parasites that feed on other insects, affecting their population (Majerus, 2009).

For these reasons, the identification of ladybirds is essential for their study, as well as for pest control. With tools such as Deep Learning models, it is possible to study their classification and the difference between their species. It is also possible to collect data on their behavior, interactions, disposition, and location (Høye *et al.*, 2020). These methods also manage to avoid the ethical controversy about the extraction of insects from their natural environment to study them (Fischer and Larson, 2019), which is necessary because of their small size, which makes it difficult to study them *it in situ*. On the other hand, this would also make it possible to identify species that could act as pests or invasive species and help determine the severity of their presence.

There are already several models for insect detection and segmentation. In the work of Ahmad, several versions of *YOLO* were tested on public datasets. *YOLOv5x* was chosen as the final model, with a *mAP* (Mean Average Precision) of 98.3%. Although, it was observed that several false negatives were obtained due to the shape and the complexity of the background of the images used (Ahmad, *et* al., 2022). In the work of Shi, different models were used for comparison, and the *R-FCNN* (Region-based Fully Convolutional Network) model with ResNet-101 was selected as the best, with 88.06% of accuracy. This model was improved using multiscale training skills and soft-MNS (Shi, *et al*., 2020). Also, in another work, several model variants were tested to detect three species of pest moths. All models were trained after transferring the parameters of trained detectors with COCO dataset. After testing the models on images of moths in pheromone traps, the best results were obtained with the *Faster R-CNN* model with a mAP of 90.25% (Hong, 2020). On the other hand, an algorithm to count insects was proposed, and for this, the detection and counting performance of 16 models were evaluated. Finally, the *Faster RCNN* model with RestNet-101, as its backbone and an input size of the images of 1024 pixels obtained the highest AP (Average Precision) with a value of 84.13% (Hong, *et al*., 2021). And in the work of Ott and Lautenschlager, a Faster R-CNN model was used to detect insects and generate bounding boxes containing them. This model obtained an AP50 (Average Precision at 50% overlap) of 90.12% (Ott and Lautenschlager, 2022).

In addition, applications for mobile devices have been developed. These applications facilitate using these models and faster identification and access to information. In an investigation, a cloud-based application was developed to automatically classify pests using a *Faster R-CNN* model with Inception V2 pre-trained with the COCO dataset. This model got an accuracy of 98%. Additionally, image preprocessing has shown to be of great importance for the improvement of results (Karar. *et al., 2021*), as in another work, where the model that shows the best results is Inception with SVD (Singular Value Decomposition) tested on a dataset in which data augmentation was performed and got a mAP of 87.99% (Shen, *et al.,* 2017).

In this work, a two-phased method for the detection and segmentation of ladybird beetles in nature is proposed. It is based on two main components, the detection step using a Yolov8 model and the segmentation step using the "Snakes" active contour model. With the Yolov8 model, it is possible to identify the regions of interest in the images (ladybird beetle regions). Then, the "Snakes" active contour model carries out the ladybird beetle segmentation precisely. We hope that combining both models can improve the ladybird beetle segmentation in nature, helping the biologist control these insects better.

2. MATERIALS AND METHODS

2.1. Database

A database with 2300 images of ladybird beetles was taken from the public iNaturalist repository (http://www.inaturalist.org), a project of the California Academy of Sciences and Natural Geographic Society. The considered dataset was the same employed in a previous work (Venegas, *et al.*, 2021), where the images belong to Ecuador or Colombia and has at least one adult ladybird. It should be noted that these images were taken under different conditions and, thus, they have various sizes and different qualities.

2.2. Deep learning models

Deep Learning is a part of Machine Learning, which is inspired by the way the brain works. It addresses trained algorithms called artificial neural networks, which after training, can make predictions that they were not programmed to make (Choi, *et al.*, 2020). The deep learning models can extract features and relations from the data they use for training and use this new information to make decisions. Image processing is at the center of deep learning, in which much progress has been made. There are several models for image processing, such as R-CNN (Regional-based Convolutional Neural Network), YOLO (You Only Look Once), Mask R-CNN, which can be used to perform object detection.

YOLO is a widely used object detection algorithm, which is known for its high accuracy and speed of detection, since YOLO uses only one neural network to predict bounding boxes and classes probabilities. In addition, YOLO make its prediction in the entire image, dividing it into a grid and making it predictions in each of them (Redmon, *et al.*, 2016).

2.3. Active contour models

Active Contour models are segmentation methods that focus on the detection of the contours of objects in images. These models start with an initially closed curve, which finds the object's edge to be segmented. This curve is made up of several points that are moving toward the object's contour with each interaction. The performance of this model depends on several parameters, such as the smoothness of the curve, the proximity to the edges of the images, and the number of points on the curve, among others (Yang, *et al., 2010*). These and organ delineation, among others (Sohn, 2011).

Several active contour models have been proposed in the field of image processing. The most known are Geodesic active contour, which incorporates geodesic information into the contour evolution process (Caselles, *et al.,* 1997). Chan-Vese active contour is a region-based active contour model that focuses on segmenting objects based on the differences in intensity values within and outside the contour (Chan and Vese, 2001). And the "Snakes" active contour model (Kass, *et al.,* 1988), unlike the Geodesic active contour and Chan-Vese models, does not explicitly incorporate the concept of region-based segmentation or the minimization of a predefined energy function. Instead, it optimizes the contour shape and position by balancing the internal and external forces (Kass, *et al.*, 1988). For the proposed model, we used the "Snakes" active contour model.

2.4. Proposed method

The proposed method is based on the combination of a deep learning-based object detector and an active contour model to accomplish the ladybird beetles detection and segmentation task. The whole procedure involves two main steps, involving the detection of the regions with possible ladybird beetles and the segmentation of the ladybird beetles presented in those regions, as shown in Figure 1. A detailed description of the proposed method is next:

- Detection phase: this phase used an overall object detector named Yolov8, based on a deep learning architecture that combines CNNs (Convolutional Neural Networks) and object detection techniques. This method uses a single neural network that takes the entire image and predicts its bounding boxes and class probabilities (Terven and Cordova-Esperanza, 2023). This phase takes the images as input and generates bounding boxes that contain ladybirds.
- Segmentation phase: this step involves the use of the "Snakes" active contour, which is a method based on the concept of energy minimization, which is the process of finding the contour configuration that minimizes the cost function, that quantifies the fitness of the contour (Kass, *et al.*, 1988). This phase uses the bounding boxes obtained in the previous step as input and segments the ladybirds. Finally, the model delivers the masks of the ladybirds.

The proposed method implementation was made in python3. The last version of YOLO of Ultralytics, the YOLOv8 was used (Ultralytics, 2023). And, to implement the segmentation model, "Snakes" active contour, the library scikit-image was used (Scikit).

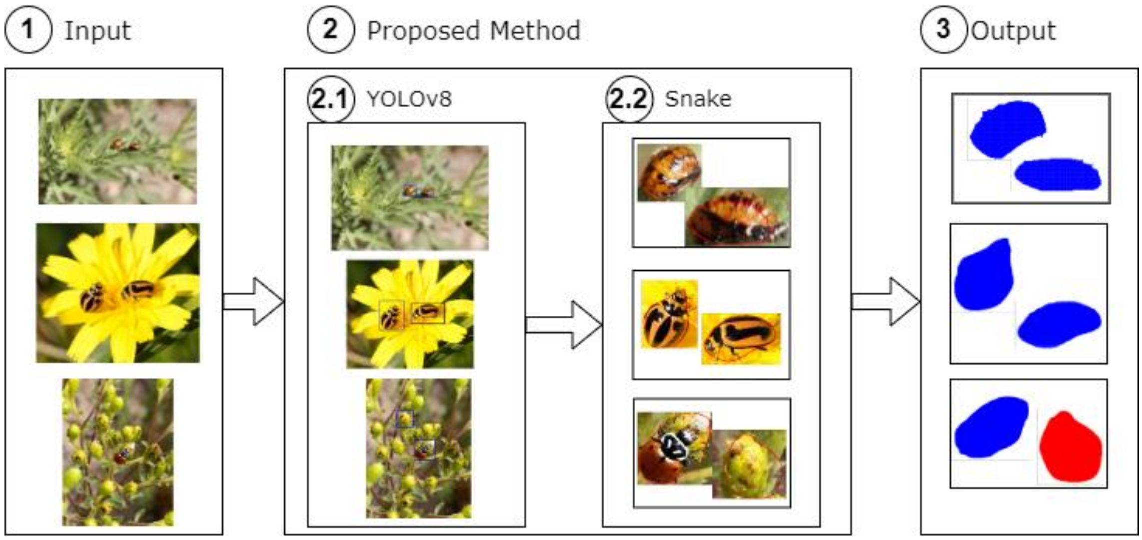

Figure 1. Proposed Model

2.5. Experimental setup

1. Data processing: All images in the dataset were processed with an Auto-Orient technique to correct their orientation, such as rotation, flips, or mirroring (Roboflow). Also, the images were converted to grayscale and normalized (each pixel of the images was divided by 255) to maintain the pixels in a specific range, from 0 to 1 (Krizhevsky, *et al.*, 2012).
2. Training and test sets: Firstly, we extract 10% of the dataset as the test subset. Then, we use the other 90% to create the training and validation sets with a stratified 10-fold cross-validation method (Berrar, 2018) for training the YoloV8 method. The cross-validation method divides the dataset into ten splits of equal size, containing the train and validation partitions. On the other hand, the test subset with 10% of the images was used to determine the generalization power of the best-trained YOLOv8 model.
3. Model configuration: The optimization of the YOLOv8 model involves 300 iterations (epochs) in training. Also, the performance accuracy on each validation partition was optimized from 0.5 to 1 to find the best trade-off between true positive and false positive detection. This fine-tuning aims to avoid

bounding boxes without ladybird beetles, which could wrongly interfere with the snake's model performance. On the other hand, the initialization points of the snake model were optimized from 100 to 500, the parameter alpha, which determines the length shape of the curve, was set from 0.005 to 0.06, and the maximum number of iterations was set from 5 to 100.

4. Assessment metrics: We use two metrics, the DICE and IoU, to assess the performance of the ladybird beetles final segmentation. The DICE metric measures the similarity or overlap between the true and predicted masks. And the IoU (Intersection Over Union) metric measures the union and intersection of the two masks (ground truth and predicted.

3. RESULTS AND DISCUSSION

3.1. Performance evaluation in training

According to the training step, the best YOLOv8 model was the one with 300 epochs and an accuracy threshold value of 0.75, as shown in Figure 2 and Figure 3. From these figures, it is possible to read that the loss value decreases when the maximum number of epochs increases. Also, the selected threshold value represents 86% of the predicted correct bounding boxes while eliminating another 86% of the false positive bounding boxes.

Regarding the best snake model, the one with 300 initial points, 100 iterations, and an alpha value of 0.01 provided a successful performance, as summarized in Table 1. From this table, it is possible to read that these parameters value were the optimal selection for the snake, providing the best DICE and IoU segmentation scores. It should be noted that the initial curve deformation in the snake reached the maximum of 100 iterations while the DICE segmentation score was increasing, as shown in Figure 4.

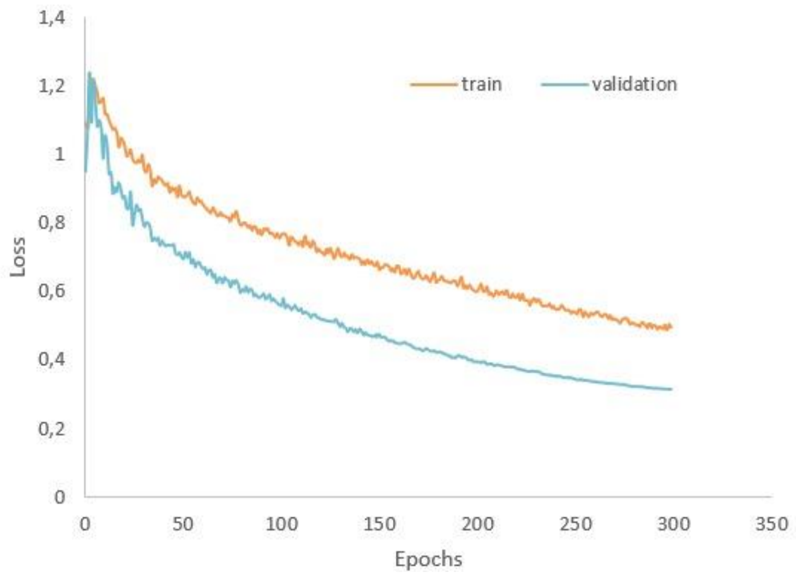

Figure 2. Box Loss Curve of YOLO Model trained with 300 epochs

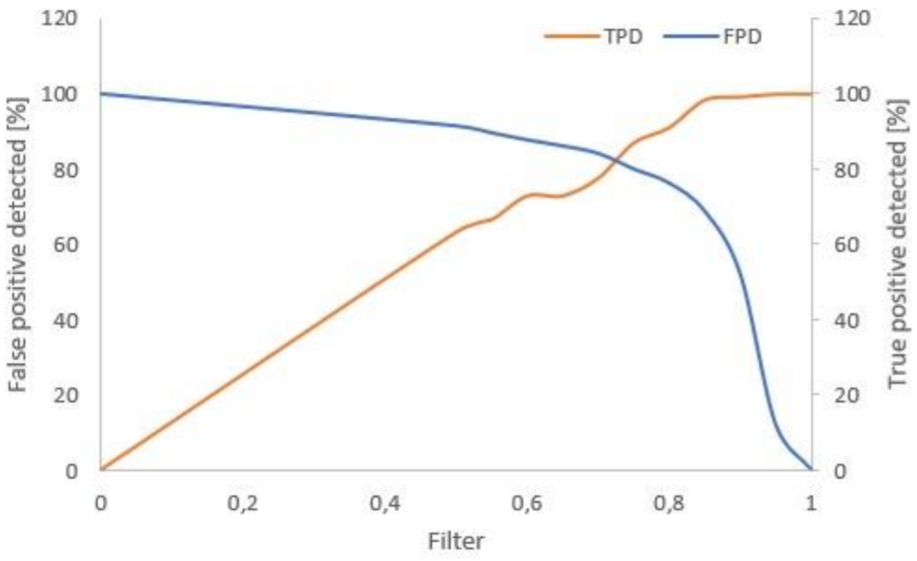

Figure 3. Filter vs NPD/TPD of YOLO Model

Table 1. Performance results of Active Contour model.

Num. Puntos	Alpha	DICE	IoU
(u)	(u)	(u)	(u)
	0.02	0.741701	0.643891
	0.03	0.698055	0.600811
200	0.04	0.655371	0.557505
	0.05	0.60854	0.512258
	0.06	0.569547	0.473167
	0.005	0.842518	0.742684
	0.01	**0.842305**	**0.743443**
	0.015	0.838012	0.739729
300	0.02	0.83019	0.730944
	0.03	0.813586	0.715148
	0.04	0.791318	0.693646
	0.05	0.775304	0.677802
	0.06	0.748231	0.650519
	0.02	0.829257	0.7283554
	0.03	0.837072	0.738415
400	0.04	0.818364	0.72067
	0.05	0.812537	0.715619
	0.06	0.799364	0.701595
	0.02	0.819564	0.726984
	0.03	0.826389	0.727354
500	0.04	0.820808	0.721697
	0.05	0.822342	0.729424
	0.06	0.817016	0.719361

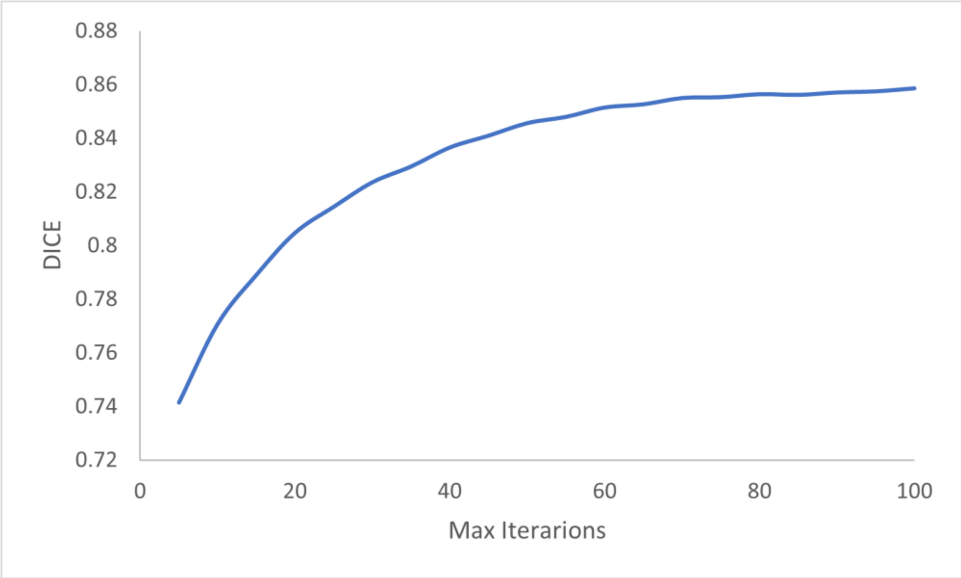

Figure 4. Max number of Iteration vs. DICE

3.2. Performance evaluation in test

The proposed method successfully detects and segments the ladybird beetles in almost all the images, as shown in Figure 5. It obtained DICE and IoU scores of 84.82% and 73.73%. These results in the test set demonstrate the effectiveness of the proposed model in accurately identifying and segmenting the ladybird beetles in nature.

From Figure 5, it is possible to observe some examples of detection using the proposed method. The model was able to generate bounding boxes containing the ladybirds accurately and segment them efficiently. However, sometimes the model introduced false-positive bounding boxes generation, causing a misleading segmentation of the snake, as shown in Figure 6. This affection is totally linked to the first part of the proposed method. Since YOLOv8 can generate false positive ladybird beetle detection, for example, flowers, stones, etc., then the second part (the snake model), does not know exactly how to find the boundary between the surrounding artifacts (foreground) and the ladybird beetles (ground truth).

In the Figure 5, the examples show that the proposed model is capable of generate the bounding boxes correctly, even though some images have a complex background. It is important to notice that most of the images have a uniform color background mostly composed of leaves. Also, the "Snakes" active contour part of the model delivers good segmentations, even though some ladybirds have different complexion.

Nonetheless, in the Figure 6, it can be seen that the possibility that the detection model generate false-positive bounding boxes is higher on more complex backgrounds, or on images where the ladybirds are smaller. For instance, more false-positive results are found in images with more presence of shadows, color contrast and other objects, generating a segmentation that only contains background and showing that the model still tries to segment the object in the false-positive bounding boxes. Yet, the segmentation of the true-positive bounding boxes is done correctly.

Figure 5. Examples of the proposed model - YOLOv8 + "Snakes" active contour

Figure 6. Examples of Wrong detection and segmentation

4. CONCLUSIONS AND FUTURE WORK

We developed a novel method based on the combination of the overall object detector YOLOv8 and an active counter model named snakes for detecting and segmenting ladybird beetles in nature. The proposed method was able to obtain a DICE and IoU score of 84.82% and 73.73% in a dataset of the iNaturalist project, respectively. These results highlighted its effectiveness and potential application in further developments that incorporate detection and segmentation tasks.

In the future, we plan to increase the training epochs of the YOLOv8 model, to decrease the number of false positive detection based on the learning process. Also, we want to increase the number of iterations in the snake deformation to improve the segmentation stage by reducing the gap between the final curve and the edge of the ladybird beetles. Moreover, expanding the size of the database could prove beneficial since the current limited number of images hampers the model's learning capacity.

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