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RESEARCH ARTICLE

Pest Detection System Based on Computer Vision for Grapevine Crops in Southern Peru

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ABSTRACT

Peru is currently the world's leading exporter of fresh grapes (SENASA, 2022), with Ica contributing 58.1% of agroexports in 2024 (COMEX, 2024). This study addresses the early detection of the most common grapevine leaf pests found in the city of Ica, using advanced machine learning methodologies, centered on the YOLOv8 model. Preprocessing and data augmentation techniques, such as reflection, rotation, scaling, contrast and brightness adjustment, were applied to diversify the training image set. In addition, an "In the wild" dataset was created, describing image capture, labeling and data augmentation, complemented with preprocessing to improve model generalization. Manual labeling highlighted key indicators of esca and spodoptera fugiperda attacks on grapevine leaves. These are pests and diseases that exist on grape leaves and greatly affect fresh grape export volumes, resulting in the excessive use of pesticide products on fresh grapes. One of the main contributions was the training through fine tuning and transfer learning of YOLOv8, integrated in a web application connected to a cloud server, improving pest detection in real time. The analysis included metrics to evaluate the accuracy and reliability of the model, obtaining 93.8% model accuracy against an unstructured dataset and mAP 50 and mAP 95 of 84% and 77% respectively.

1. INTRODUCTION

Peru's wine industry is highly relevant worldwide, being the largest exporter of fresh grapes (SENASA, 2022). In the valleys of Ica, 49 grape varieties are grown, highlighting the varieties Red Globe, Sweet Globe, Sweet Celebration, Flame Seedless and Candy Dreams (SENASA, 2023). In 2022, Peruvian grape exports reached 53 international markets, including the United States, the Netherlands, Hong Kong, Mexicoand China. However, compliance with sanitary and phytosanitary requirements is key for these exports, asgrapevines are vulnerable to diseases caused by viruses, bacteria and fungi, which can reduce their productivity and cause significant economic losses (Mohamed K, et al., 2018).

One of the main challenges facing Peruvian viticulture is the spread of pests, such as Spodoptera fugiperda,known as codling moth, which affects various crop species, including grapevines. This pest causes significant damage by feeding on leaves and bunches, affecting photosynthesis and increasing the vulnerability of crops to fungal infections such as Botrytis cinerea and diseases such as ESCA, which can reduce production by up to 60% (Sun, 2023; Souza et al., 2024). Poor management of these pests, often due to lack of technical advice, has led to excessive and ineffective use of pesticides, which not only affectsproduct quality, but also alters the ecosystem and reduces the volume of exports by exceeding permitted pesticide residue limits (Castillo, 2020).

To address this problem, several technological solutions have been developed. Obasekore et al. (2023) implemented a robot with computer vision for pest detection, achieving efficient integration using neural networks such as Google Net, Alex Net, InceptionV3 and ResNet, with an accuracy rate of 97.1% and an average detection time of 0.21 seconds. On the other hand, Hernandez-Calvario et al. (2022) used deep learning algorithms for counting agave plants from aerial images, improving the accuracy in detecting infected plants. In addition, Murat et al. (2022) implemented Logit layers and SVM kernels in the classification of grape leaves, achieving an accuracy of 97.6% with the use of the cubic kernel.

Despite these advances, a significant lack of studies on computer vision applied to agronomy in Latin America has been identified. In particular, the detection models used in previous research have been trainedwith structured and small volume datasets, which limits their effectiveness (Obasekore et al., 2023). Therefore, this research proposes to create a proprietary dataset in Ica, using unstructured data, and to trainmodels for early identification of pests in Red Globe and Sweet Globe grape varieties. It is also suggestedto explore the use of generative adversarial models (GAN) to improve the detection of plant diseases usingsynthetic images (Mike, 2023). Research such as that of Gonzalez-Fuentes et al. (2023) has demonstrated the importance of innovative technologies, such as the use of pheromones, for early pest detection, underscoring the need for comprehensive approaches to infestation monitoring and control. This study addressed the early detection of the most common grapevine leaf pests found in the city of Ica, using advanced machine learning methodologies, centered on the YOLOv model.

2. METHODOLOGY

The research was developed in three methodological blocks. In Block 1, the model was trained using a dataset created from the capture of pest images. The pre-trained model was adjusted with this dataset to improve its performance. In Block 2, the focus was on model validation, which included preprocessing thedata to remove noise, followed by fine-tuning of the classification model, optimizing its ability to accurately identify pests. Finally, in Block 3, a computer vision system was designed for real-time detection,developed in software that uses a camera to capture the images and apply the trained model. Since the collected images presented noise, a segmentation was implemented to improve detection, adjusting the structure of the dataset to allow a more accurate identification of pests by the model and the structure of thedataset.

2.1 Model training stage:

Figure 1 shows the flow that was followed to perform the training stage of the model in detail.

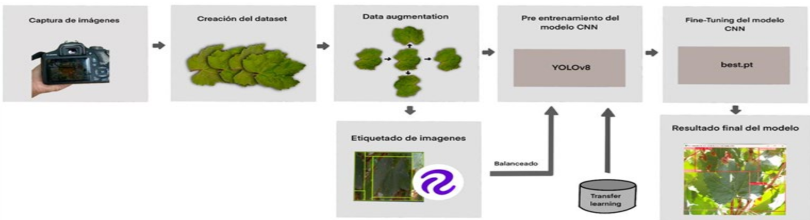

Figure 1: Flow diagram of the model training stage.

2.1.1 Creation of the dataset:

In this section we visualize this specifications of the own dataset are visualized through some images collected in the city of Ica, the area where the research was oriented.

Table 1: Specifications pest dataset

Dataset	Registrations	Population	Specifications	Variables
Own Dataset	13,284	Ica-Peru	-Total images: 7,000 -Images of vine leaves with disease: 2,461 -Images of vine leaves with blight: 1,060 - Images of healthy leaves: 3,479 -Number of images obtained by data augmentation:6,284	Leaves according to disease or pest, Healthy leaves

			-image resolution: 1200x1600 - Image format: JPG	

Table 1 presents the total volume of images collected for each dataset, including those added by data augmentation techniques to balance the data. This set of images is critical for training the YOLOv8 model, allowing for greater accuracy in pest detection and ensuring that both healthy and contaminated vine imagesare properly balanced. Images with data augmentation are also key to model testing, improving detection capability. The dataset was built following a field study in the Villacuri Valley, Ica, where 3521 images ofvines with pests and 3479 healthy ones were captured using three different cameras: a Canon EOS-Rebel, a GO-pro and an iPhone 14 Pro, all configured to capture images in high-resolution formats and with variability, in contrast to more structured datasets.

In addition, the vineyard in Ica has an aligned design of rows of vines supported by posts and wires, whichfacilitates the orderly growth of the vines and optimizes exposure to sunlight. This layout favors the passage of agricultural machinery for tasks such as pruning, harvesting and phytosanitary treatments, improving vineyard productivity. Drip irrigation ensures efficient water distribution, while regular pruning improves fruit quality. Bird protection nets are also used to prevent crop damage, contributing to efficient vineyard management.

Figure 2: Image capture

Figure 2 shows the difference between images captured in a structured environment and those obtained ina real environment, such as the dataset of this research. Images from the real environment, with higher noise and complexity, are more representative for training models intended for use in real situations, improving their capability in real-time sensing applications. In contrast, models trained in controlled environments, although accurate during training, tend to generate errors or false positives when applied in real conditions,due to the lack of representativeness of the supervised environment.

Figure 3: Comparison of structured and unstructured images

Once the images were captured, we proceeded to classify the images according to the type of pest, diseaseand healthy leaves. In this way, observations were made in front of the leaves that had to be labeled and separated by folders for better balancing of the dataset data. Table 4.1.1.2 shows details of the methods usedfor the classification of vine leaves, based on the previously mentioned steps.

Table 2: Sheets with classification by type

Hojas con Spodoptera Fugiperda	Hojas con ESCA	Hojas Sanas
		

2.2 Data augmentation

As shown in Figure 4, the variation from a single image through to five different ones with the use of data augmentation is randomized. This reflects, more accurately, how the application of data augmentation wasperformed in the research. This is of utmost relevance in the research, because as previously mentioned, this will help to generate a balance of the data, to obtain a balanced dataset with adequate data volume forthe application.

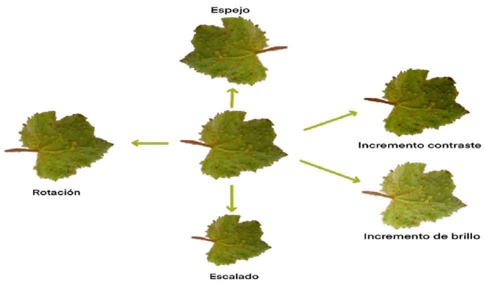

Figure 4: Image augmentation with data augmentation

Table 3 shows the specific variations according to each data augmentation technique that was applied to the images to obtain a larger volume of normalized data.

Table 3: Data augmentation methods and limits

Techniques	**Lower Limit**	**Upper limit**
Reflection (Mirror)	-	-
Rotation (degrees)	-45º	45º
Scale (%)	50%	150%
Contrast enhancement	-30	30
Increased brightness	-21	21
Increased saturation	-15%	15%

2.3 Image labeling:

Image labeling was performed in RoboFlow, highlighting key areas such as spodoptera fugiperda attack, esca and healthy leaf zones, in order to optimize the performance of the YOLOv8 model, which considers the 'background' as a default class to reduce false positives. For this purpose, the background of the imageswas manually labeled as a healthy zone, preserving relevant data in this unstructured dataset. The process, based on object detection and supervised learning techniques, involved the participation of experts to ensurethe accuracy and consistency of the annotations. In addition, a cross-check between labelers was implemented to ensure labeling quality, with a detailed database recording all decisions. This rigorous approach facilitated the development of accurate algorithms for the detection of spodoptera fugiperda and esca on grape leaves. As shown in Figure 5, the images were manually labeled in bounding boxes, reflectingthe attack of spodoptera fugiperda on grapevine leaves.

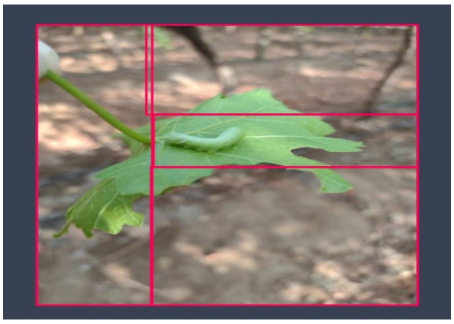

Figure 5: Manual image labeling

2.4 Yolo v8 model training

In this research, a data distribution was designed where 60% of the images are for training, 20% for testingand the remaining 20% for validation. These data cover three scenarios: healthy leaves, leaves affected by Spodoptera Fugiperda and leaves with ESCA. Two deep learning algorithms are applied in these cases to detect pests and diseases, because some images show mixed infestations. The training and validation process is optimized by cross-validation, using an integrated data set and running the model for 120 epochswith batches of 60 images. This allows evaluating the accuracy and efficiency of the model in early detection of pests and diseases, comparing the performance of computer vision algorithms in multi-target segmentation.

The classification model used is YOLOv8, recognized for its ability to detect objects in real time. This highly efficient model applies an Ada optimizer and a loss function that evaluates coordinate accuracy, confidence level and classification predictions. The YOLOv8 architecture is organized into three main components: the backbone, the neck and the head. The backbone performs convolutional operations to extract features from images at different scales, while the neck uses the SPPF technique to fuse multilevel information. Finally, the head performs predictions, refining locations and classifications, optimizing object detection and minimizing losses to ensure maximum model performance.

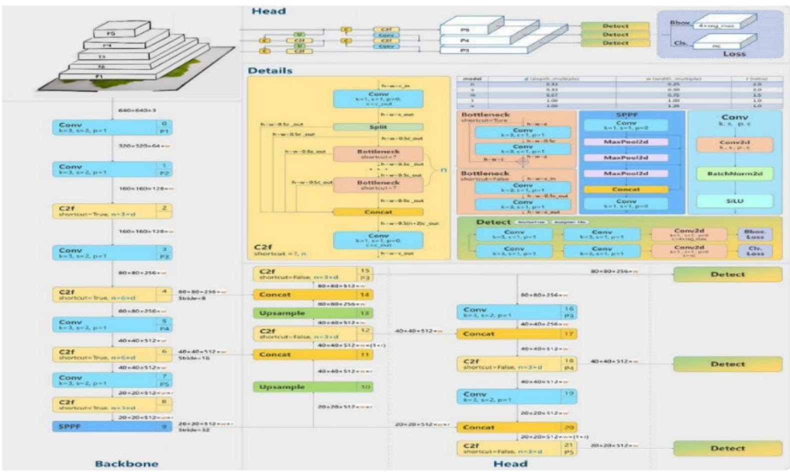

Figure 6: Architecture adapted from Yolov8

2.5 Model validation stage:

In this stage, an image preprocessing algorithm is applied for background reduction, with a segmentation method, in order to refine the model accuracy and reduce background data losses, which is a detection feature of the YOLOv8 model. Figure 7 shows the flow followed to perform the model training stage in detail.

Figure 7: Flowchart of the model validation stage.

In the preprocessing stage, balancing and data augmentation techniques were applied to the dataset to balance the images of healthy and infected leaves, avoiding biases in the model. Using Data Augmentation, variations of the Spodoptera Fugiperda-affected leaf images were generated, enriching the dataset without the need for additional captures. A key technique was Image Segmentation with Background Reduction, which removed irrelevant elements and allowed the model to focus on the essential features of the pests, optimizing both accuracy and the training process. This was crucial in complex agricultural environments, where the background varies considerably due to vegetation, soil and lighting. To this end, semantic segmentation was used by applying pixel classification of the images into leaf, pest and background categories, which allowed isolating the areas of interest by effectively eliminating the background of the image as visualized in Figure 8.

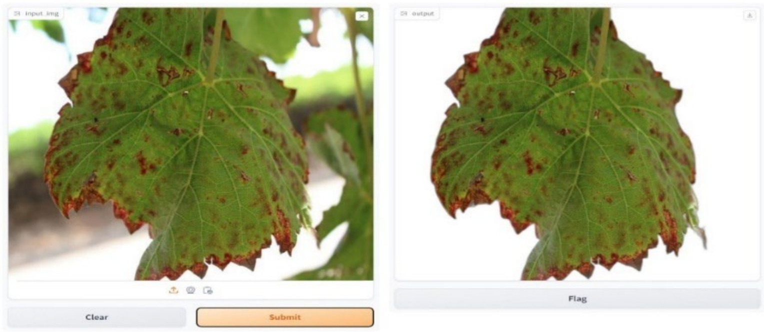

Figure 8: Background reduction

In the model application stage, the preprocessed data were used to validate the trained model with the newlyobtained data, selecting the Best.pt file, which represents the best performance after several training iterations. This choice was based on hyperparameter optimization and cross-validation, ensuring a robust and efficient model. In the image classification phase, the trained model was implemented for automatic detection and classification in a real-time environment in Villacurí, Ica. Metrics such as Accuracy, Recall, Specificity and IoU were used to evaluate its performance, analyzing its accuracy and ability to identify pests without generating false positives. These metrics facilitated the comparison of models and the identification of the best balance between accuracy and efficiency, providing a comprehensive evaluation for informed decisions on their use in the field.

2.6 Software quality testing:

The pest detection system is based on the implementation of the YOLOv8 deep learning model, optimizedto identify pests in grape crops in real time. Using advanced computer vision techniques and a dynamic web interface, the model has been tuned by Fine Tuning, resulting in the best.pt version, which representsthe most accurate iteration of the training. A resolution of 640x640 pixels was selected to balance accuracyand processing speed, with a confidence threshold of 60% to minimize false positives, ensuring fast and reliable responses in agricultural monitoring. The model is integrated into the directory models of the mobile application, facilitating its use in the field.

2.6.1 Integration of the model with the detection system

The model was implemented through an application developed in Flask, designed to interact with mobile device cameras or webcams. This application allows the capture of images in real time and the loading of previous images, facilitating a detailed analysis in agribusiness. With a minimalist and user-friendly interface, optimized for use in the field, users can capture images directly from crops or upload documentsprepared by experts, so that the model processes the images and detects pests immediately. This approach contributes to more accurate pest management, reducing the overuse of pesticides and promoting more sustainable agricultural practices.

2.6.2 System evaluation and testing

The system also includes a software testing framework to ensure proper operation prior to field deployment. These tests were implemented to validate the accuracy of the software in various conditions and configurations, ensuring that the system is robust and reliable in its performance. It is important to mentionthat the main focus of the tests was on the Integration Tests, because they demonstrate the operation of thesystem as a whole, giving a clear view of the system performance in close to real conditions.

2.6.2.1 Smoke testing

In this study, smoke tests were conducted to validate the functionality and performance of a web application for detecting pests on grape leaves. Basic operability was tested, such as the correct loading of the main page, the image upload form and the display of results. Subsequently, using Python's unittest framework, key aspects such as YOLOv8 model load time, interface accessibility, processing time, and error handlingunder multiple requests were evaluated. These tests helped identify and optimize potential bottlenecks, ensuring optimal and stable performance in the final system deployment. The automation of these tests strengthened the reliability of the system and provided a basis for future improvements.

2.6.2.2 Unit testing

Unit tests were designed and executed using the unittest framework to ensure the correct functioning of theindividual components of the grape leaf pest detection web application. Using unittest.mock to simulate external interactions and flask to test the application in a controlled environment, aspects such as the availability of the main page with HTTP 200 status code and the correct loading and image processing functionality were validated through simulations with BytesIO. These tests also evaluated the robustness of the system to incorrect or empty entries, ensuring appropriate error messages in such cases. Additionally,the ability of the application to capture images in real time by simulating the use of a camera was tested, and the correct initialization of the YOLOv8 model was verified, as well as the ability to handle multiple image loads consecutively. These tests ensured that the system could operate in dynamic environments withmultiple simultaneous users, allowing seamless interaction between image capture and the detection model,essential for use in the field.

2.6.2.3 Integration testing

In the integration phase of the grape leaf pest detection project, integration tests were performed to validatethe interaction and operation of the system components, using flask_testing and the requests library. First,basic server functionality was tested using a GET request, ensuring that the main page loaded correctly with an HTTP 200 status code and the text 'Upload image'. Then, the system's ability to process images was evaluated by sending files through requests.post and verifying the generation of results with elements suchas 'result.html' and 'static', confirming the correct creation and storage of processed images.

Error scenarios, such as loading invalid or empty files, were also tested, ensuring clear responses such as 'No image selected'. In addition, the robustness of the system was evaluated against large images (5000 x 5000 pixels) created with PIL.Image, testing its ability to process high-demand requests. Finally, the persistence of the results was verified by extracting the path to the processed image and confirming its accessibility with a GET request returning a 200 status code. These tests ensured that the application functioned effectively as a cohesive system, from the web interface to the image processing backend.

2.6.2.4 Functional tests

Functional testing focused on the deployed web system with the objective of evaluating the effectiveness of the model and its performance in various scenarios. For this purpose, test cases were developed using Orthogonal Arrays, as detailed in Table 4, resulting in six specific cases to implement. These cases were formulated using the Gherkin language for ease of understanding. The combination of these cases provided a total of six test cases necessary to evaluate all possible situations that could be encountered in a real operating environment.

Table 4: Combinatorial cases with Orthogonal Array

Case	Entrance	Resolution	Format	Lighting	Sheet Type
1	Image uploaded	Low resolution	JPEG	Well illuminated	Healthy leaf
2	Captured image	Low resolution	PNG	Poorly illuminated	Leaf blight
3	Image uploaded	High resolution	JPEG	Well illuminated	Leaf with disease
4	Captured image	High resolution	PNG	Poorly illuminated	Healthy leaf
5	Image uploaded	Low resolution	JPEG	Well illuminated	Leaf blight
6	Captured image	High resolution	PNG	Poorly illuminated	Leaf with disease

3. RESULTS

The present research shows the results of the training tests carried out with the objective of having a betterview of the model and being able to make a better comparison of the results based on the initial objective of the research, that is, the detection of the pest in grapevine crops in the city of Ica.

It is important to mention that to date the results of the algorithms are based on the previous training of themodels, and not on a final result. Therefore, it may vary according to the training time acquired by the model and the test images that enter the model. Similarly, based on the results obtained in Table 5, Figure 11 shows a better comparison between the two models.

3.1 Yolov8 model results

Table 5: Normalized confusion matrix

ESCA	0.92		0.01	0.20
SANO	0.02	0.95	0.03	0.42
SPODOPTERA	0.01	0.01	0.81	0.28
BACKGROUND	0.05	0.04	0.15	
	ESCA	**SANO**	**SPODOPTERA**	**BACKGROUND**

Table 5 shows the percentage results for the detection of ESCA, Spodoptera fugiperda and healthy leaves.With the current data, it stands out that the accuracy of the model for the detection of healthy leaves and ESCA with 95% and 92% respectively, which show greater accuracy for Spodoptera fugiperda, which maybe due to the volume of data and the almost imperceptible presence of this pest physically in grapevine crops.

Figure 8: Sample of prediction on validation data

As can be seen in Figure 8, the labels made by the YOLOv8 model and its prediction percentage for diseasesand pests in grapevine crops are shown. As the prediction for each individual image is observed, the resultis higher compared to the confusion matrix, due to the fact that its focus is explicitly on the results of each approach, with previously expressed labels. Based on this, remarkable results are shown in the model, before the detection of the healthy zones of the plant, as well as the ESCA disease and the spodoptera fugiperda pest.

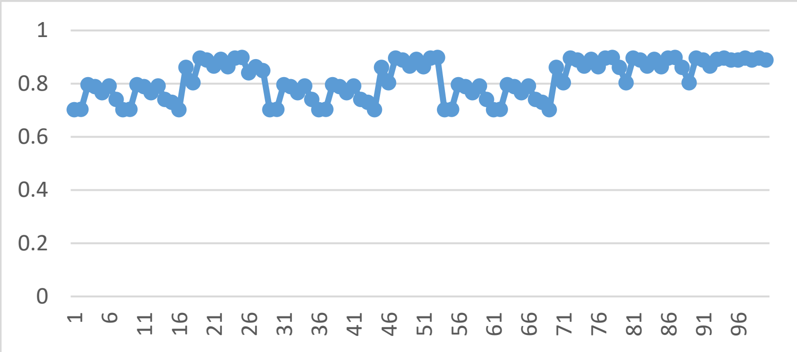

Figure 9: Accuracy graph

It is with Figure 9 shows the accuracy metrics of the model and how it is improving with each epoch that isrun. As previously mentioned, 120 epochs with 60 batches were used to obtain better training results.

Similarly, for Figure 10, in the case of Recall, the growth of improvement is also visualized for each trainingrun by the model.

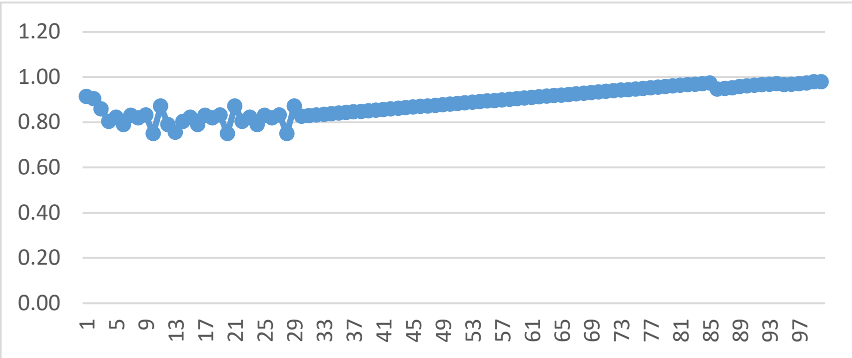

Figure 10: Recall chart

Table 6: Results of mAP-50 and mAP-95

Class	Imag es	Instance s	mAP 50	mAP 95
All	1214	2380	0.84	0.77
Esca	1214	578	0.81	0.76
Healthy	1214	1371	0.94	0.82
Spodoptera	1214	431	0.76	0.72

As can be seen in Figure 11, the IoU validation data is shown, with the mAP 50 and mAP95 metrics. Regarding the mAP50, an average of 84% accuracy can be seen for all classes with respect to the original label framing compared to the model prediction, the same for sano with 94%, spodoptera with 76% and Esca with 81%. In the case of road mAP of 95% effectiveness, lower accuracy is visualized because the approach is based on a percentage of detection effectiveness equal to the model greater than 50% accuracy.This can be visualized in the same way in Figure 10, with a more increasing perspective with respect to each model run.

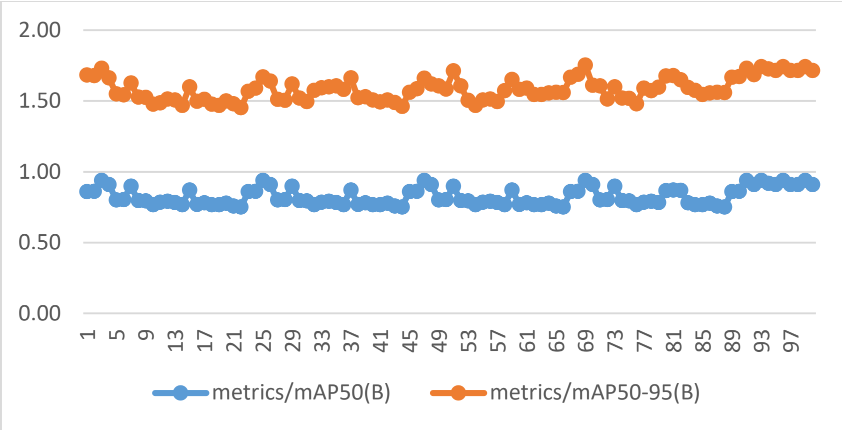

Figure 11: IOU Graph

3.2 Detection system results

This section shows the results obtained in the web application developed for real-time pest detection.

Figure 12: Result in the detection system

Figure 12 shows the web application interface, with one of the images captured in real time in the southernpart of the country, specifically in the Villacurí valley of the city of Ica. It can be observed that, at the moment of capturing the image with the camera, a connection is made with the model to perform the detection and the labeling of the image can be visualized to indicate the percentage of prediction, which inthis case is 89%, the classification box of the zone in which the pest is detected and the name of the pest that is being identified. It is important to mention that the percentages in the web application show a higherpercentage of accuracy compared to the results of the confusion matrix, which can be seen in section 3.1, because, when performing the detection in a unified way, that is, in a single image, the result will be higherthan when performing it in a larger volume of data.

Table 7: Smoke test results

Metrics	Result	Unit
Home page load time	1.5	Seconds
Home page loading success	Success	.
Image loading time	2	Seconds
Image upload success	Success	.
Results display	Success	.

Table 7 shows that the smoke tests demonstrated high integrity in the web system, providing a quick validation of the basic functionality of the system from an overall perspective. The results were efficient, with load times of 1.5 and 2 seconds for the main page and image loading in the system, respectively. In addition, the tests confirmed the correct validation of image loading and proper data visualization, pointingto a successful integration of the model to the web system and the correct functionality of image loading for subsequent predictive analysis.

Table 8: Unit test results

Metrics	Result	Unit
Total number of tests	7	-
Past tests	7	-
Failed tests	0	-
Code coverage	95	%
Execution time	0.8	Seconds

Table 8 shows that the unit tests, executed individually on each component of the system, yielded positive results in all instances, confirming the adequate functionality of each element with a 100% pass rate. Thesetests covered approximately 95% of the web system code, concentrating mainly on essential functionalities.With an average execution time of only 0.8 seconds, this result is considered fast and efficient, demonstrating that each component operates correctly in isolation. This suggests that there should be no problems during the integration phase, as the components have demonstrated their reliability independently.

Table 9: Integration test results

Metrics	Result	Unit
Home page load success rate	100	%
Upload success rate and image detection	98	%
Average response time for image loading	2	Seconds
Rate of correct handling of invalid files	100	%
Correct empty file handling rate	100	%
Success rate in handling large files	95	%
Consistency in multiple loads	99	%
Persistence rate of results	100	%

Table 9 shows that the integration tests revealed a high level of reliability in the web system, with a 100% success rate in loading the main page and 98% in loading and detecting images. The average response timewas 2 seconds, demonstrating efficient performance. The system correctly handled invalid and empty files,and although the success rate when processing large files was 95%, this suggests a possible area for improvement. In the simulation of 50 simultaneous connections, the application maintained 99% efficiency, demonstrating its robustness in stress tests. In addition, perfect persistence and accessibility of all processedimages was guaranteed.

Table 10: Functional test results

Case	Result	Accuracy	Processing time
1	Success	95%	1.5 seconds
2	Failure	75%	1.5 second
3	Success	100%	3 seconds
4	Success	98%	2 seconds
5	Success	90%	1.5 seconds
6	Success	97%	2.5 seconds

Table 10 shows a robust performance of the system, with 83.4% of the cases resulting in complete successand one failed case representing 16.6%. It was observed that factors such as low illumination and image resolution negatively affected detection accuracy, while high resolution and well illuminated images provided the best results. Processing time remained consistently low, averaging 2 seconds per image, demonstrating the efficiency of the system even under varying conditions.

4. DISCUSSION

With respect to the results of the present study, the effectiveness of the YOLOv8 model in pest detection stands out, where it achieves an accuracy of 93.8%, a recall of 89.3%, together with a mAP50 of 84% anda mAP95 of 77%, which can be visualized in Table 11. These results not only reflect an excellent balance between accuracy and recall, but also exceed the capabilities of previous versions and variations of the model, such as YOLOv7 and YOLOv8l, and are competitive with other well-known models such as YOLOv8m and YOLOR. In addition, it is important to note that the YOLOv8 model, in the present research, was applied in an own dataset "In the wild", that is, when presenting background noise, this can reduce the level of accuracy of the model because it has its own layer called "background", which detects the background and in some images, the background presented relevant information for testing.

4.1. Comparison with the literature review

Unlike previous models, YOLOv8 introduces significant improvements in accuracy and speed, which is critical for implementation in real-time applications. Furthermore, in previous research, the models were trained with structured datasets in a regulated environment, so this may have changed when training the current model. Despite this, the incorporation of attention mechanisms such as SimAM and advanced structures such as the VoV-GSCSP network in YOLOv8 improve the discrimination of objects in complex backgrounds, an area where previous models showed limitations. The following table compares the resultsof YOLOv8 with previous studies and other versions in similar contexts, as shown in Table 11.

Table 11: Results of YOLOv8

Model	Accuracy (%)	Recall(%)	mAP50(%)	mAP95 (%)	Application	Authors
YOLOv8 Adapted	93,8	89,3	84	77	Pest detection	This study
YOLOv8m	90,6	76,5	86,7	65	Pest detection	Sun et al.,2024
YOLOv8l	91,6	77,4	83,9	69,1		
YOLOv7	92	85	72	-	Pest detection	Pinheiro et al., 2023
YOLOR	93	83	76	-		
YOLOv8	89,3	64,7	47,4	28	Object detection	Talib et al.,2024
IDP-YOLOv9	84,7	80,9	70,4	-	Object detection	Li et al., 2024

Compared to previous versions and similar models, YOLOv8 Adapted shows significant improvements. For example, while YOLOv7 and YOLOR, previous models in the series, present an mAP50 of 72% and 76% respectively, YOLOv8 achieves an mAP50 of 84%. This increase is indicative of optimizations in theYOLOv8 architecture, which enable more efficient and accurate detection in complex scenarios. Particularly, YOLOv8m, although with a slightly lower mAP95 than YOLOv8, exhibits a superior mAP50of 86.7%, highlighting its efficiency in detection at different scales. This demonstrates that YOLOv8m maybe preferable in applications where large-scale detection is more critical than extreme accuracy in detail, bearing in mind that this model was trained in a structured environment.

In addition, YOLOv9, although with a lower overall performance compared to YOLOv8, is still relevant for its robust and adaptive approach. This model reviewed in the research of Li et al. (2024), presents a scenario of aerial image capture by drone, which may have affected the accuracy and efficiency results as it is a more complex scenario. Finally, the YOLOv8 model was considered for object detection in the research of Talib et al. (2024), because it presents results significantly inferior to the model of the present research, despite being a model applied to a non-structural environment. Therefore, the superiority of the Adapted YOLOv8 model over these models is not only manifested in performance metrics but also in adaptability for real-time detection applications, which is crucial for automated pest monitoring and management. This capability enables fast and accurate decision making, essential for operational efficiencyand sustainability in crop management.

5. CONCLUSIONS

This study has demonstrated the effectiveness of the YOLOv8 model in the early detection of pests in grapevine leaves in real time, providing a valuable tool for agriculture in Ica, Peru, where pests represent a significant challenge to agricultural productivity. The results obtained underline YOLOv8's ability to process images with high accuracy, taking advantage of advanced computer vision and deep learning techniques. In addition to presenting a layered structure, focused on accurate and fast detection, which is relevant in a real-time image capture scenario. The integration of the model in a web application connected to a cloud server has enabled real-time detections, considerably improving the capacity to respond to infestations. In addition, the implementation of a proprietary dataset in an unstructured environment has provided greater relevance to the research due to its peculiarity and approach to a real unstructured simulation environment.

The adaptation of YOLOv8 with fine tuning techniques to specifically recognize Esca and Spodoptera fugiperda on grapevine leaves has been shown to be an effective strategy, achieving optimal levels of accuracy and reliability, facilitating rapid and effective crop management decisions. This approach will notonly reduce reliance on pesticides, but also promotes more sustainable farming practices, allowing large volumes of grapes suitable for export to continue to be produced.

6. FUTURE JOBS

Despite the promising results, this study faces limitations, including the number of images captured for theSpodoptera Fugiperda pest, which had lower data volume compared to the other detailed classes in the dataset. Future research could expand the scope of the dataset to include more pest varieties and environmental conditions to test the robustness of the model under different scenarios.

Additionally, it is suggested that the implementation of deeper neural networks or the exploration of new architectures could offer improvements in detection speed and accuracy. Finally, further studies are proposed to evaluate the implementation of this technology in other crops of economic importance for Peruand the region and to implement an aerial image capture system, which could significantly expand the impact of computer vision tools applied to modern agriculture. Continued progress in this line of research is vital to address global challenges such as food security and agricultural sustainability.

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