Artificial Intelligence-based Detection of Fava Bean Rust Disease in Agricultural Settings: An Innovative Approach

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***Abstract*—The traditional methods used to identify plant diseases mostly rely on expert opinion, which causes long waits and enormous expenses in the control of crop diseases and field activities, especially given that the majority of crop infections now in existence have tiny targets, occlusions, and looks that are similar to those of other diseases. To increase the efficiency and precision of rust disease classification in a fava bean field, a new optimized multilayer deep learning model called YOLOv8 is suggested in this study. 3296 images were collected from a farm in eastern Morocco for the fava bean rust disease dataset. We labeled all the data before training, evaluating, and testing our model. The results demonstrate that the model developed using transfer learning has a higher recognition precision than the other models, reaching 95.1%, and can classify and identify diseases into three severity levels: healthy, moderate, and critical. As performance indicators, the needed standards for mean Average Precision (mAP), recall, and F1 score are 93.7%, 90.3%, and 92%, respectively. The improved model's detection speed was 10.1 ms, sufficient for real-time detection. This study is the first to employ a new method to find rust in fava bean crops. Results are encouraging and supply new opportunities for crop disease research.**

Keywords—Fava bean disease; deep learning; YOLOv8; real-time detection

I. Introduction

Humanity faces a severe problem with food security, and one of the main challenges to agricultural output is the occurrence of plant diseases [1]. These diseases generate significant losses, making early identification of these situations crucial. Accurate diagnosis of plant diseases is essential to minimizing economic losses imposed on them. The three approaches now in use are manual inspection of a plant's leaves to determine its health condition and the sort of illness it is affected, which has time, efficiency, and high professional needs issues; pathogen testing [2], which is correct but time-consuming and unsuitable for field detection, and plant protection expert diagnosis [3], which is subject to personal interpretations and has low accuracy.

Development of artificial intelligence and machine vision in various sectors, including agriculture is required. It states that many researchers prefer hyperspectral images due to their capacity to provide continuous spectral information and the spatial distribution of plant diseases [4]. Near-infrared spectroscopic digital images are also used for plant disease detection [5]. However, the tools needed to capture spectral images are costly and not easily accessible. Digital cameras and mobile phones are within everyone's reach; on the other hand, they make it simple to capture visible light images, making them a more practical choice for image recognition research.

Deep learning (DL) is a crucial technique to remedy this problem. While resolving complex issues like feature extraction, transformation, and image classification, this technology helps implement new tools, methods, and technologies in agriculture. By proposing detection models based on convolutional neural networks (CNN) and using photos taken by cameras, many researchers have used deep learning to identify crop diseases in real time. Therefore, DL has enormous potential to increase the effectiveness of agricultural output and lower losses brought on by plant diseases [6].

To detect rust disease on fava bean pods, this study used the convolutional neural network's enhanced version, You Only Look Once (YOLO). It is commonly used in computer vision tasks, including object segmentation and image classification [7]. A grid divides images into cells, with each cell responsible for object detection in the YOLO object identification approach. For the first time, a bean crop rust disease was detected using the innovative system named YOLOv8 in this study. This research aimed to identify and correctly classify rust disease according to three different severity levels: healthy, moderate, and critical, using images obtained with the camera.

The YOLOv8 method has many advantages over traditional object identification techniques. We want to solve the limitations of current methods and offer a more efficient and accurate solution for the recognition of rust disease in our study. One of the main advantages of the YOLOv8 approach is its excellent level of precision, making it ideal for operations involving identifying small objects. It locates items of interest more precisely by utilizing innovative techniques, including bounding boxes, multi-scale prediction, and feature fusion. This increased accuracy is crucial for applications requiring reliable and precise detection results. Real-time performance is one of this strategy's key benefits. In our application, which tracks the progression of plant diseases in real-time, accurate recognition of small objects in real-time video streams is critical. This is made possible by YOLOv8's exceptional processing rates, which are made possible by an efficient network design and parallel processing. Additionally, YOLOv8 shows that it can manage various environmental factors, including occlusions, changing illumination, and crowded backdrops. The method's adaptability in the real world, where environmental variables are frequently unpredictable, is enhanced by its capacity to retain dependable detection performance in challenging settings. The suggested solution's streamlined operational model is shown in Fig. 1.

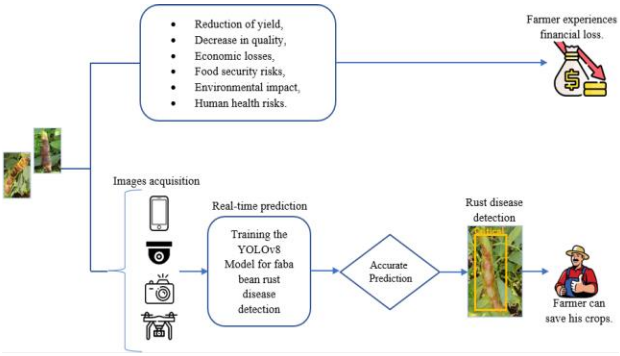

Fig. 1. Creation of the operational model for crop health monitoring.

The context of deep learning algorithms in plant disease detection is discussed in Section II of the seven sections of the research paper—the background in Section III. We outline the methods and materials in Section IV. In Section V, we outline our contribution and the experiment results. The results are discussed in Section VI; Section VII is where we conclude and outline our next steps.

II. Related Works

In this section, we summarized some algorithms proposed by researchers and are recently used for disease detection in crops. We can cite Dai et al. [8] work as an example. They merged the CBAM attention mechanism, HRNet, and ASPP structure to enhance the R-CNN. With an average identification rate of 88.78%, a detection algorithm was presented to remove tiny target pests of diverse sizes in citrus.

Karthik et al. [9] recommended a two-level deep-learning method to detect tomato leaf disease. The second deep learning model was applied as an attention mechanism on top of the first model after the first was used to learn critical features via residual learning. The authors identified the late blight, early blight, and leaf diseases in tomatoes using the PlantVillage dataset.

To identify the unhealthy region on tea leaves with an average accuracy of 83%, Mukhopadhyay et al. [10] suggested a new approach based on image processing technology. Zhao et al. [11] proposed a YOLOv5s-based model for crop disease detection. To enhance global and local feature extraction and address the issue of scaling the prediction frame during model learning, the model uses an upgraded CSP structure, CAM structure, additional grid, and DIoU loss function. The model has a recall of 87.89%, an F1 score of 0.91, and an average accuracy (mAP) of 95.92%. The model also has a 40.01 FPS detecting speed. When employed by Alita et al. [12] to find plant leaf diseases, the EfficientNet deep learning model outperformed other cutting-edge deep learning models in terms of accuracy. To show and detect insects in soybean crops in real-time; the authors Tirkey et al. [13] of this research suggest a deep learning-based approach. They used YOLOv5, InceptionV3, and CNN to achieve 98.75%, 97%, and 97% accuracy as they investigated the viability and dependability of transfer learning models. With YOLOv5, the suggested solution runs at 53 frames per second.

III. Background

Fava bean rust disease presents a severe risk to fava bean crops worldwide, significantly decreasing crop quality and productivity. Traditional approaches to rust disease detection and control rely on visual examination and human observation, which can be time-consuming, labor-intensive, and prone to mistakes. Computer vision and machine learning developments have made deep learning models that can automatically detect and classify rust diseases possible. The YOLOv8 (Fig. 2) object identification method is one such model. This model is a development of the YOLOv4 model, renowned for its object detection speed and accuracy. With the help of a deep neural network and several convolutional layers, the YOLOv8 model can recognize and categorize objects in real time. The YOLOv8 algorithm can quickly and effectively identify this disease since it was trained on a large dataset of healthy and rust-infected fava bean leaf images. The model can evaluate the severity of an infection, which may be used to choose the best preventative actions. The YOLOv8 model, which may decrease reliance on human inspection and improve the speed and accuracy of diagnosis, significantly advances the detection and control of fava bean rust disease.

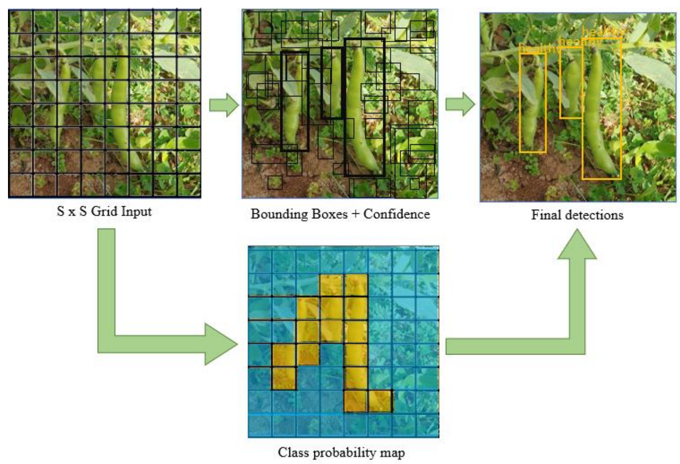

Fig. 2. Pipeline of YOLOv8 algorithm.

IV. Materials and Methods

A model for fava bean rust disease detection in crops is presented in this paper. To do this, an AI-based image recognition system is created. The suggested technique will help farmers apply pesticides precisely and quickly, cut operating costs, and enhance crop output and quality. The settings, data collecting, data pre-processing, Data annotation, and deep learning model training are just a few components of the system's structure. The system uses the trained model to identify rust diseases and validate the developed models based on the results obtained. The suggested strategy is expected to give farmers precise information for effectively managing crop disease. Fig. 3 depicts the proposed method's flowchart.

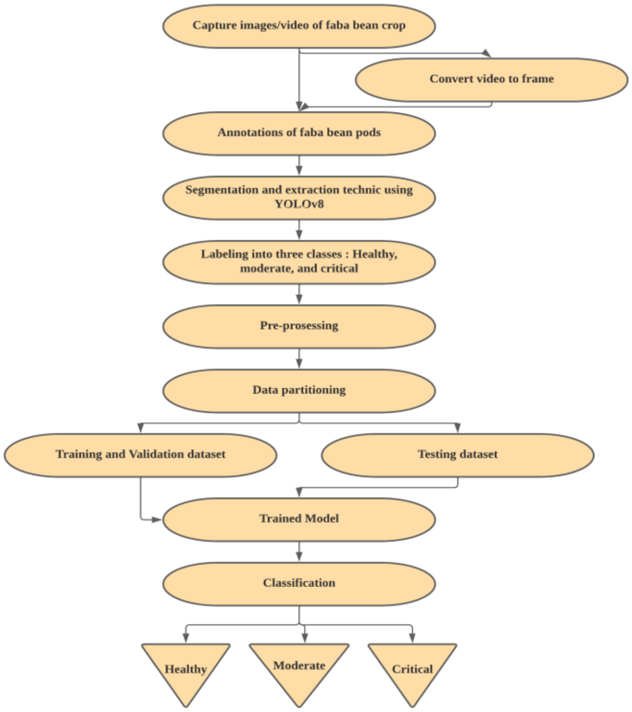

Fig. 3. Diagram showing the proposed model's workflow.

A. YOLOv8 for Object Detection

The YOLO family of detection models, which has become famous for their precise detection and segmentation abilities [14], now includes the new YOLOv8 model. This new model's architecture comprises a backbone, head, and neck. Given its transformed architecture, enhanced convolutional layers (backbone), and more sophisticated detecting head, it is an excellent solution for real-time object detection.

One of its strong characteristics is this model's ability to recognize many objects in an image or video faster and more accurately than prior iterations. Because of the model's giant feature map and enhanced convolutional network, which boosts accuracy and speed and are supported by our results, it is more effective than prior versions. The architecture and framework of the best-trained model YOLOv8l are shown in Fig. 7 and divided into multiple vital parts, each of which is outlined below:

- Backbone network: used by the YOLOv8 model to extract features from the input images. YOLOv8 uses the cross-stage partial network (CSPNet) design for the backbone network to lower the computing cost of the network while keeping its accuracy [15].
- Neck: The neck acts as a connecting point between the backbone and the detection head. The channel is specifically constructed using the spatial pyramid pooling (SPP) module, which uses different-sized pooling processes to collect multi-scale information [15].
- Detection head: Predicting the bounding boxes and class probabilities of things seen in the input image is the responsibility of the detection head. It does this by predicting each item's bounding boxes and class probabilities using a series of convolutional layers, followed by a cluster of anchor boxes [15].

B. Research Site

The experimental location was examined at a farm in Ahfir, Berkane province, eastern area of Morocco, at coordinates 34°57'58.9 "N 2°07'42.5 "W shown in Fig. 4. The Fava bean crop was the subject of the investigation, and the picture capture plots were chosen randomly.

C. Images Acquisition and Data Collection

To capture images, a Sony DSLR-A230 camera was used. In Table I, the camera settings are displayed. Horizontally aligned pictures were taken. The position of the lens was between 30 and 50cm away from the fava bean pods during image collecting, having a pixel resolution of 3872 x 2592. Throughout March and April 2023, pictures were shot every three to four days.

Three types of fava bean pods—healthy, moderate, and critical—are included in the dataset used for this research; in Fig. 5, samples of each class are displayed. These photos were taken in several spots within the same agricultural area. 1124 images are included in the healthy pod, and 1279 in the moderately infected pod—893 photos of the pods with severe infections. There are 3296 images in all in the data collection.

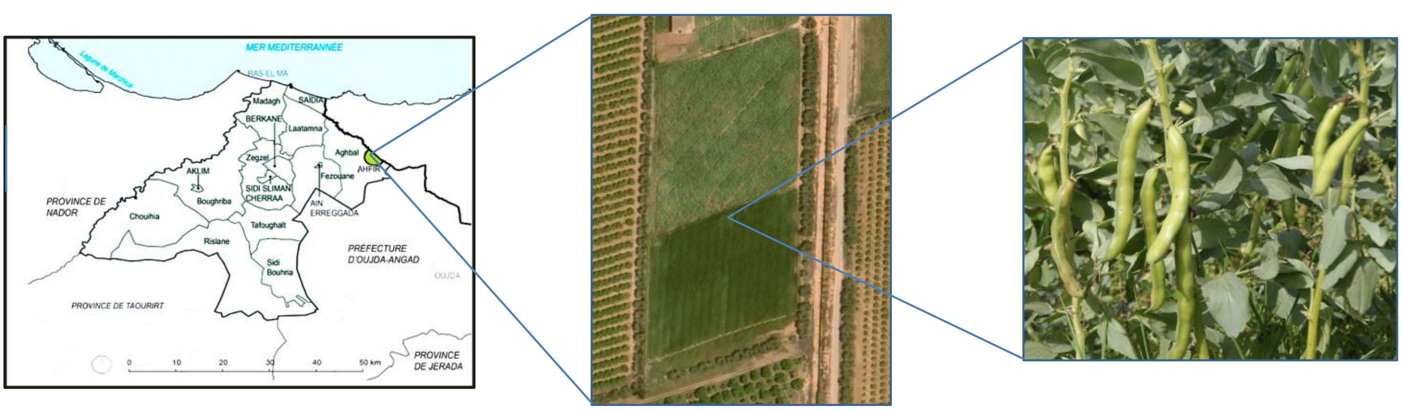

Fig. 4. Research area located in Ahfir, Berkane province, Morocco.

TABLE I. SONY DSLR – A230 CAMERA

Camera Lens	ISO Speed	Resolution	Max Aperture
Sony/Minolta Alpha APS-C 18-55MM Lens	ISO 3200	3872 x 2592	9.4 feet at f/3.5

(a) Healthy (b)Moderate (c)Critical

Fig. 5. A sample of each class in our database.

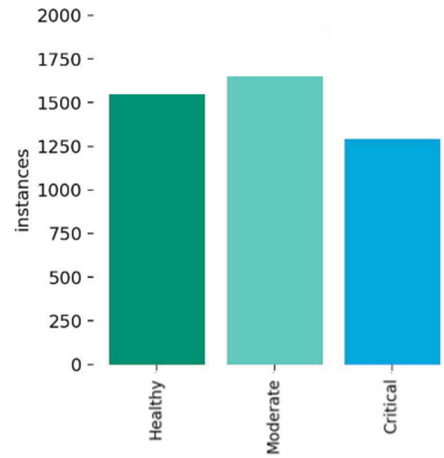

Fig. 6. Number of instances per class. There are labels for 1540 healthy, 1682 moderate, and 1246 critical pod samples.

D. Data Annotation

Before training our model, it is crucial to complete this step, which requires carefully labeling the images from the resized and obtained data set. This technique is executed via the Python-written "LabelImg" graphical image annotation program [16], which was used for image normalization. The training and validation set images were annotated in VOC format to obtain XML and Txt files with the image names, sizes, class names, target image positions, and other data. Fig. 8 displays the data for the annotations.

The accuracy of the training dataset has a significant effect on how well a machine-learning model performs. An agricultural specialist who helped us find the various lesions present in the farm field to take captures and assisted us with the computer annotation was crucial in our study's dataset annotation. We identified 4468 lesion boundary boxes from a collection of 3296 images. Particularly, healthy, moderate, and critical pods totaling 1540, 1682, and 1246 labels were identified, respectively, (Fig. 6). Since all annotation files were saved in ".txt" format, the model can readily access and understand them.

According to this stringent, expert-guided annotation procedure, the YOLOv8 model can now be trained on high-quality data. This also increases the model's accuracy and efficiency in finding rust diseases in fava bean crops.

E. Augmentation of Dataset and Data Preprocessing

Fig. 6 shows a slight disparity between the healthy and critical classes and the middle class, which might lead to overfitting and impact our model's ability to identify and classify data accurately. Therefore, the training set for healthy and critical pods is increased using simple adjustments like rotation, zoom, brightness, and color saturation of the images to balance our dataset. Additionally, adaptive scaling and filling procedures were conducted on the pictures of the various fava bean pod instances before training our model. The input image size was 640x640 pixels.

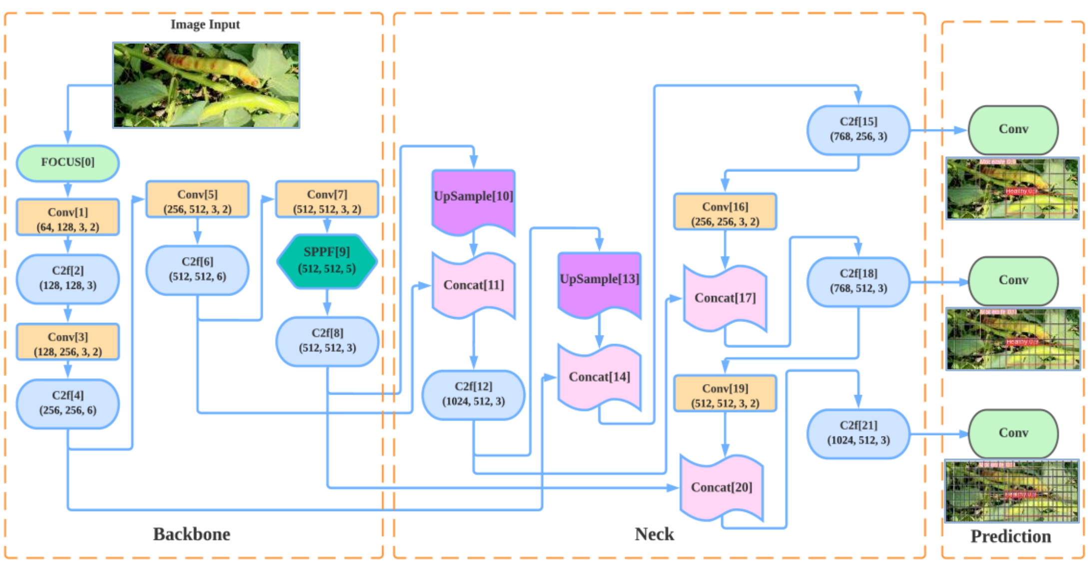

Fig. 7. Architecture of YOLOv8l – best-trained model.

F. Experimental Setup

The processing platform was a desktop PC with Windows 10 Professional running. The Torch version was 1.13.1, the CUDA version was 11.6, and the Python version was 3.9. The hardware consisted of an Intel® Xeon® W-2223 CPU with a 3.6 GHz core clock, 16 GB of RAM, and an NVIDIA GeForce Quadro P1000 graphics card.

The dataset was divided into training and validation sets in a 4:1 ratio after each image, and the status of the bean pods was manually annotated. Six distinct architectures, including YOLOv8s, YOLOv8l, YOLOv8x, YOLOv5s, YOLOv5l, and YOLOv5x, were modeled using the training set. Four batches of 8 photos each were used for the training procedure. The goal was to evaluate the performance of each architecture and identify the most effective identification model for rust disease detection in fava bean crops. The best model for rust disease detection in fava bean crops was chosen based on the architecture with the highest performance. Fig. 7 shows the selected model's architecture.

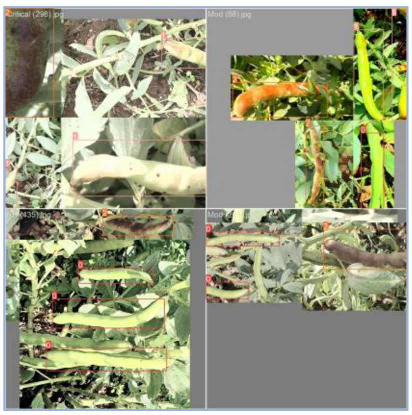

Fig. 8. Images annotation result.

The best hyperparameters were used in the training models. The momentum parameter for the SGD optimizer, which was used in the model learning process, was set at 0.937. This study uses the SGD optimizer; therefore, the convergence will be too slow if the model's initial learning rate is higher. As a result, the learning rate was initially set at 0.01 and gradually increased to identify the ideal answer more quickly during the final stage of model training.

The number of training epochs is 40, and the input training picture size is 640x640. The training hyperparameters for our architecture model are listed in Table II.

TABLE II. HYPERPARAMETER OPTIMIZATION FOR IMPROVED MODEL PERFORMANCE

Hyperparameters	Yolov8l
Initial learning rate	0.01
Final learning rate	0.01
Optimizer	SGD
Momentum	0.937
Weight decay	0.0005
Warmup epochs	3.0
Cls	0.5
IoU	0.7

V. EXPERIMENTAL RESULTS AND COMPARATIVE ANALYSIS

A. Indicators for Evaluating the Model's Performance

Several indicators and assessment specifications were used to judge the performance of the trained models to ensure they could provide accurate object detection results. Examples include the number of network parameters, Precision (P), mean Average Precision (mAP), Recall (R), and speed of detection. The intersection over union (IOU) threshold value was set to 0.7 for our dataset. The conventional formulae (1), (2), (3), (4), and (5) were used to figure out the values of P, AP, mAP, R, and F1, respectively [17]. Using these assessment measures, we could compare the accuracy and efficiency of several models and assess how well they performed under different situations. Using these criteria, we could choose the top-performing model for rust disease detection in fava bean crops criteria.

$$Precision = \frac{\text{True Positive}}{\text{True Positive+False Positive}}\ x\ 100\% \tag{1}$$

$$AP = \int_0^1 Precison(Recall)d(Recall)\ x\ 100\% \tag{2}$$

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP\ x\ 100\% \tag{3}$$

$$Recall = \frac{\text{True Positive}}{\text{True Positive+False Negative}}\ x\ 100\% \tag{4}$$

$$F1\ Score = 2\ x\ \frac{Precision\ x\ Recall}{Precision+\ Recall}\ x\ 100\% \tag{5}$$

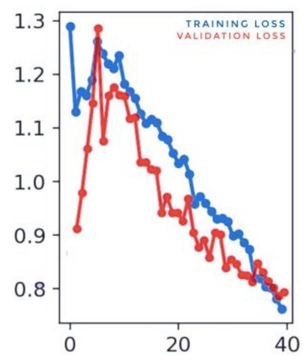

Fig. 9. Graphical representation of model training and validation sets.

B. Models Training

The various architectures of the YOLOv5 and YOLOv8 models were chosen for training, validation, and testing. With a learning rate of 0.01, SGD was used as an optimizer. The four distinct structures of the YOLOv5 model are YOLOv5s (the smallest), YOLOv5m, YOLOv5l, and YOLOv5x (the biggest). The YOLOv8 model includes four structures—YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x. Six YOLOv5 and YOLOv8 architectures were selected for our study. Table III displays the parameter comparison. The mAP of YOLOv8l was 0.937, which was 7.79% higher than the mAP of YOLOv5l, and 20.2% higher than the mAP of YOLOv5s. However, YOLOv5s improved the execution speed due to the reduced number of network layers and parameters but with less accuracy. Therefore, YOLOv8l has the advantage of being more accurate, which meets the needs of this study.

TABLE III. COMPARISON OF THE PARAMETERS OF THE YOLOV5 AND YOLOV8 MODELS AND GENERAL EVALUATION METRICS LIKE PRECISION, MAP, AND SPEED

Model	Params	Precision	Recall	mAP	mAP50@95	Speed (ms)	FLOPs (B)	FPS
YOLOv5s	~07.2M	75.2%	68.9%	74.8%	45.6%	**2.8**	**7.2**	**358**
YOLOv5l	~46.5M	81.4%	79.2%	86.4%	48.8%	7.9	109.1	126.6
YOLOv5x	**~86.7M**	88.6%	87.6%	88.7%	69.6%	13.8	205.7	73
YOLOv8s	~11.2M	89.9%	**90.3%**	91.8%	72.7%	4.8	28.4	209
YOLOv8l	~43.7M	**95.1%**	89.5%	**93.7%**	**76.5%**	10.1	164.8	100
YOLOv8x	~68.2M	93.2%	88.9%	93.6%	75.9%	15.4	257.4	65

YOLOv5s has improved execution speed by 2.8 ms, which is 41.7% faster than YOLOv8s and 81.9% faster than YOLOv8x due to its reduced number of network layers, parameters, and memory requirements. However, it also has reduced accuracy and mAP. The accuracy of YOLOv8l was 0.951%, which is 2% higher than the accuracy of YOLOv8x, and 20.9% higher than the accuracy of YOLOv5s. Therefore, YOLOv5s has the advantage of being fast but less accurate, whereas YOLOv8l has observable accuracy, which better meets the needs of this study. The initial model for this experiment has been chosen to be Yolov8l. The verification measures described the performance of this model. Fig. 9 shows the total training and validation losses for each epoch.

To evaluate the impact of training intervals on model performance, the YOLOv8l architecture was developed in this work to visualize the process of dynamic training state monitoring and model function. The results are displayed in Fig. 10. The model's parameters changed significantly when it was iterated from 0 to 14 epochs. The score eventually stabilized during the 30–40 epochs. After 30 to 40 model epochs, the index stabilized, and the precision (P) increased to around 95.1% before stabilizing.

The loss functions that our trained model employed for its detection and classification tasks are thoroughly examined in Fig. 10. The stochastic gradient descent approach optimizes the network and modifies its parameters during the learning process, decreasing the value of the loss function. We see a significant link between the value of the loss function and other performance indicators like precision, recall rate, and average precision. Classification loss measures how well an algorithm can predict a specific item category. Since classification accuracy increases as the loss value decreases, minimizing the loss function value is essential for better accuracy.

A set of test images was chosen, as shown in Fig. 11, to better prove how well the trained model identified the rust disease on fava bean pods. This picture shows how the model selected for this investigation can accurately locate disease positions, classify them based on pod state, and successfully avoid missed and false detection issues for small and many targets.

The classification performance of the proposed model is clearly shown by the confusion matrix shown in Fig. 12. The model works efficiently in terms of detecting accuracy for all types, and it makes it simple to analyze the accuracy for each target class. The model's excellent accuracy is a promising result and shows that it can be used successfully in situations found in real-life situations.

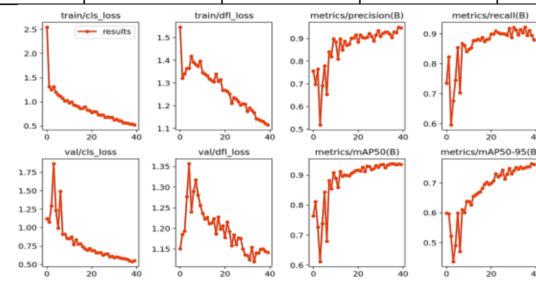

Fig. 10. Visualization of training progress and model evaluation metrics, between 0 and 40 epochs.

An essential tool for assessing the efficiency of classification model performance is the confusion matrix. Fig. 12 illustrates the confusion matrix for the model used to examine the target classes' classification accuracy. The values of true positives, true negatives, false positives, and false negatives for each class are displayed in the confusion matrix. With the bulk of values near or above 0.9, the model's identification accuracy is good for all classes. With a score of 0.95, the model specifically proved good accuracy for the "healthy" class, demonstrating its ability to accurately discriminate healthy samples from other classes. With a score of 0.88, the "moderate" class also showed high accuracy. With an accuracy of 0.94 for the "critical" class, the model was able to successfully detect samples with severe conditions. These findings are encouraging for the proposed model since they show that it can correctly classify samples into multiple categories. The model may be used in real-world applications for disease detection and classification, enabling prompt and efficient interventions to treat the diagnosed disorders, according to its high accuracy in all categories.

Fig. 11. Rust disease detection images on fava bean pods, (A-F) represent test images of the proposed model with different accuracy.

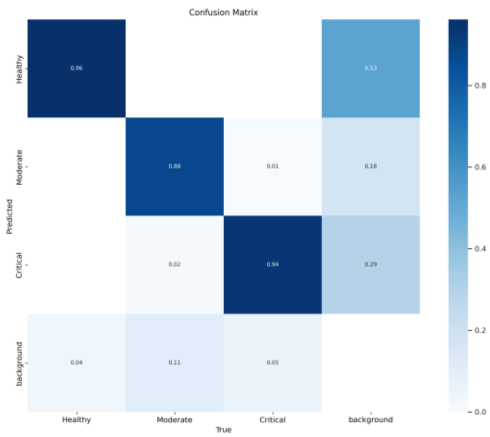

Fig. 12. Confusion matrix of the trained model – YOLOv8l.

The F-measure is the weighted harmonic average of the precision (P) and recall (R) of a classifier using the F1 score. The confidence value in the graph shown in Fig. 13 is 0.681, which maximizes recall and precision and corresponds to the maximum F1 value of 0.92. In general, a higher F1 score and confidence value are preferred.

According to the results displayed in Fig. 14, a precision value of 1.00 is included in the 0.983 confidence range for effect. With bigger data sets, the estimate becomes more correct, and the confidence interval shows how confidently we can state the effect magnitude.

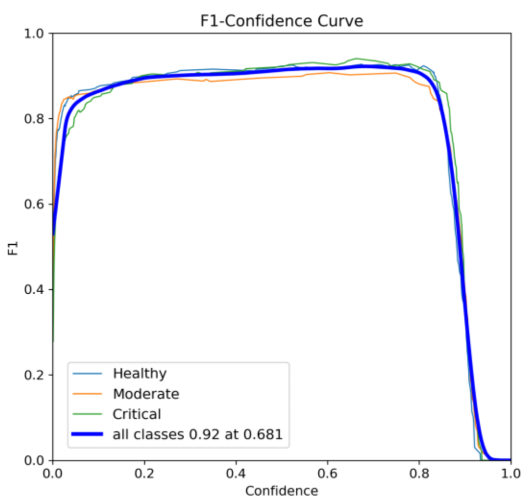

Fig. 13. Performance evaluation of YOLOv8l model using F1 curve.

The sample size is often a key element in assessing accuracy. As demonstrated in Fig. 15, the recall value and associated confidence interval are objectively understood together. Recall values of 0.000 are included in the confidence interval of 0.96. The significance of sample size and confidence intervals for appropriately reporting and interpreting recall levels in this experiment is illustrated by these results.

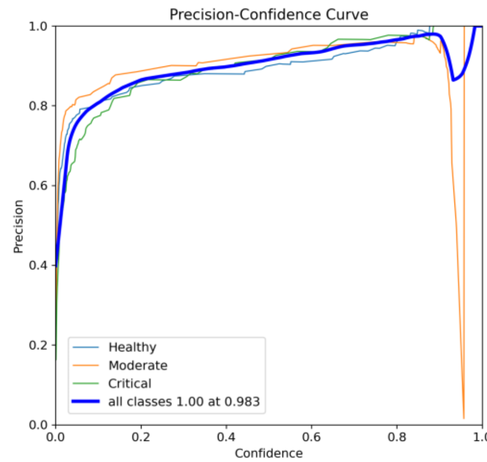

Fig. 14. Model performance through precision curve.

Finally, the curve in Fig. 18 illustrates the link between recall and precision at various thresholds. High recall and low false negative rates are correlated with high precision and low false positive rates, respectively. Excellent recall and excellent precision are both shown by a large area under the curve. Utilizing the precision-recall curve, we discovered 0.937 mAP.

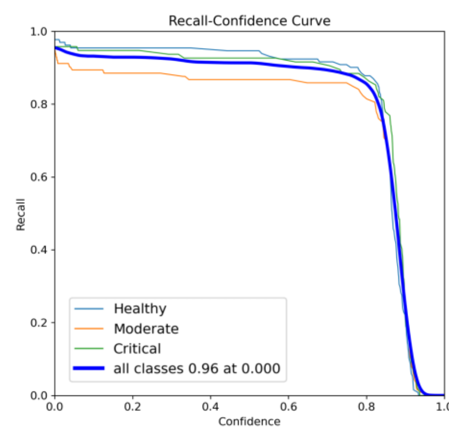

Fig. 15. Recall curve for model performance evaluation.

VI. Discussion

In this work, in comparison to other models from the same family or to other versions of YOLOv5 (Fig. 16), we proved the YOLOv8l model's capacity for detecting rust disease in fava bean pods. The model exceeds the average accuracy reported by previous studies in identifying the presence of a single or a lot of classes, with an accuracy of 95.1% and a mAP of 93.7%. Given the necessity of quick recognition of diseases for efficient crop management, Fig. 17 illustrates several real-time experiments conducted on fava bean pods in the agricultural field. To confirm its accuracy and efficiency, it was tested in a variety of situations; the performance of the system and its capacity to precisely and consistently detect fava bean pods' condition have been providing light on using the proposed YOLOv8l model, which has offered important details. This study is special since it is the first to use a deep-learning model to identify fava bean pod rust disease.

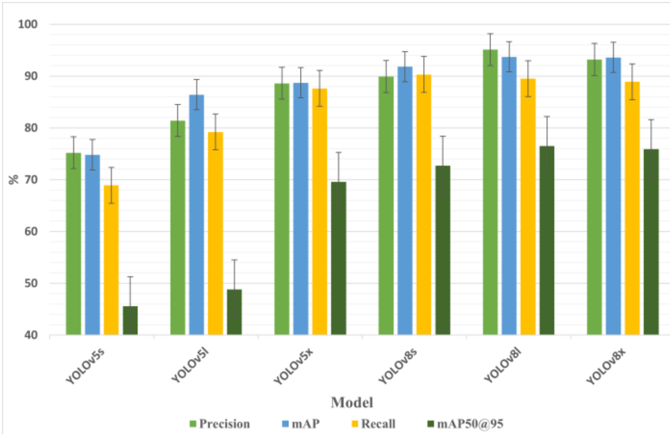

Fig. 16. Performance comparison of yolov8 model with other models.

Three distinct categories of rust disease conditions—healthy, moderate, and critical—are included in the dataset used for this investigation. However, by expanding the dataset for a generalization of the model, our application may still be improved. The effects of our treatment on different crops and illnesses will be fascinating to see. The creation of advanced real-time detection models based on moving robots with integrated cameras through agricultural fields is another research area and future direction. Farmers could be able to monitor their crops more effectively and correctly as a result, and the demand for human labor for disease detection might decrease.

Fig. 17. Results of testing the proposed solution from different time of day – Yolov8l model.

Our study proves our suggested method's improved plant disease detection and categorization performance. We have significantly improved precision, efficiency, and speed using the YOLOv8 architecture, exceeding traditional methodologies in related research disciplines. As can be seen, our findings are superior to those of earlier research, setting a new standard for illness detection precision. Our method surpasses detailed results reported in [18]–[25] and achieves a remarkable mAP of 93.7%, demonstrating the suggested model's excellent generalizability and resilience. Furthermore, our recall of 89.5% is higher than the value stated in [25], highlighting the efficiency and dependability of the suggested approach. Our YOLOv8-based solution also exhibits impressive speed, with an average image detection time of only 10.1ms, reaching 100 frames per second (FPS), satisfying real-time requirements, and obtaining a good rust disease detection result, surpassing the performance of [20], [22], and [25]. Our work demonstrates the vast potential of the YOLOv8 model for precise and effective rust disease classification, exceeding the findings of previous research efforts regarding the accuracy, recall, mAP@0.5, and F1 score. Our study significantly contributes to agricultural disease research by emphasizing these improvements, opening the door for more investigation and future advancements in this crucial area.

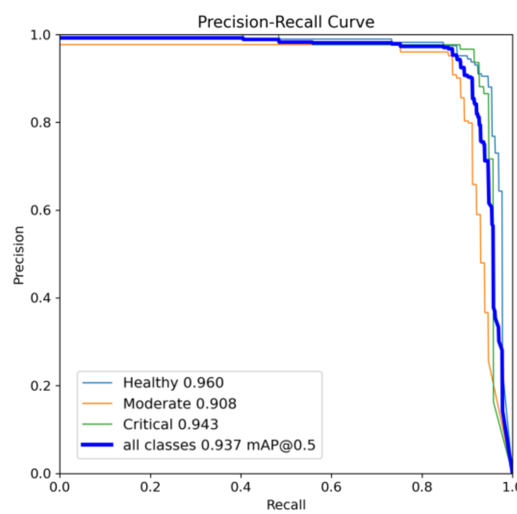

Fig. 18. Precision-recall (PR) curve.

We want to discuss inherent limitations that are pertinent to the findings of our research. It is essential to note right away that our dataset was only collected from a single farm in eastern Morocco, which may restrict the applicability of our findings to other geographic areas or different agricultural techniques. As a result, care should be used when extending our findings to other situations. Additionally, even though we tried to gather a comprehensive dataset of 3296 images, it's vital to understand that this representation does not fully capture the range of variety and nuance connected with fava bean rust illness. As a result, our suggested deep learning model, YOLOv8, may perform differently when subjected to a wider variety of field circumstances. Because our model showed good identification accuracy, it is essential to understand that no model can be without errors and that the chance of misclassification or false positives cannot be eliminated. Finally, it is critical to remember that despite being judged suitable for real-time detection in our experimental setting, the detection speed of 10.1ms may vary depending on the hardware and computer capabilities available in other agricultural scenarios. Understanding these restrictions helps us fully appreciate our study's scope and applicability. It also emphasizes the need for more research to address these limitations and improve the precision and robustness of AI-based disease detection mechanisms in agricultural settings.

Our work does not address identifying and categorizing other plant diseases; instead, it focuses only on the rust disease in fava bean harvests. Future research should focus on the efficacy and usability of the YOLOv8 model in detecting illnesses other than rust in various crops. We intend to present a thorough and open overview of our findings by fully outlining these limitations. We think pointing out these limitations will help researchers interpret our results more accurately and create foundations for more studies and advancements in crop disease identification.

VII. Conclusion

To evaluate the severity of the rust disease on fava bean crop pods in natural settings with small, dense, and overlapping crop targets, this research proposes an advanced comparative study between six different YOLOv5 model iterations and the most modern YOLOv8 model. By using many layers, the deep learning-based technique automates the image processing and feature extraction processes in the deep learning model. It is significant to highlight that the database used in this study was built especially for it. The data is typical of real-life situations because the images were taken on a farm where fava beans were cultivated. For the model to be trained successfully, collecting information was done carefully to ensure image quality and diversity. This database can be used to train other models and is an excellent resource for detecting agricultural diseases in future research. The study's results proved the superior performance and resilience of the proposed YOLOv8l model. This provides a foundation for the model's execution on embedded devices, robots, or mobile devices. The model could accurately detect the three different classes of fava bean pod conditions with a remarkable accuracy of 95.10%, with better identification of smaller pod targets and complex situations. By integrating more courses into the dataset and using various optimization strategies, we will continue to improve the structure and the features of the model provided in this study to increase its robustness and expand its use cases.

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