Advanced Algorithmic Model for Real-Time Multi-Level Crop Disease Detection Using Neural Architecture Search

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Abstract. Efficient crop disease management shows great promise in optimizing the agricultural industry. Accurate identification of infection levels is crucial for implementing effective and efficient disease treatments. However, accurately identifying and locating crop diseases in complex, unstructured field environments remain challenging. This necessitates the utilization of large volumes of annotated data. This research paper comprehensively evaluates deep transfer learning techniques for identifying the degree of rust disease infection in Vicia faba L. production systems. We curate a vast dataset comprising images captured under natural lighting conditions and at different growth stages of the crop under study. We propose a deep learning model based on Neural Architecture Search (NAS) specifically designed for early detection and accurate classification of disease levels in crops. We compare the performance of our proposed model with nine other deep learning models using transfer learning. Remarkably, transfer learning based on the NAS method achieves high classification accuracy, consistently exceeding 90.84% F1 scores. Moreover, all models exhibit short training times, requiring less than 3 hours. Among the evaluated models, our NAS-based model emerges as the top performer, highlighting the importance and effectiveness of this method in developing state-of-the-art models. It achieves a mean average precision of 94.10% and an impressive overall recall of 96.96%. These results significantly contribute to developing robust and accurate disease management strategies, paving the way for improved agricultural practices and increased crop yields. Our approach enables early disease detection and precise classification, leveraging deep transfer learning and facilitating timely interventions and optimized treatments. With the help of this study, we can now better utilize cutting-edge agricultural technology, paving the way for sustainable crop production in the future.

1 Introduction

Determining crop diseases is essential for effective pest management and reducing income loss in the agriculture industry [1]. Applying efficient management techniques is made

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possible by accurately identifying pests and the damage they cause [2]. Based on the categorization of leaf images, several technologies and methods, including deep convolutional neural networks (DCNN) and transfer learning, have been utilized to diagnose crop illnesses [3][4]. These models can differentiate between healthy and sick leaves; some can pinpoint the impacted crop species. Plant diseases must be identified early to stop them from spreading and reduce their harm to food safety and agricultural productivity [5]. Nonetheless, there are still issues with plant disease detection that must be resolved. Crop disease identification using transfer learning algorithms has gained popularity in agricultural informatics. Deep learning methods, particularly convolutional neural networks (CNN), have been successfully applied to classify plant diseases based on leaf images. Several studies have explored the transfer learning capabilities of CNN architectures such as VGG16, ResNet50, EfficientNetV2S, Densenet201, Xception, InceptionResnetv2, and RetinaNet [6][7]. These models are trained on large labeled datasets like ImageNet and achieve high accuracy in detecting and categorizing various plant diseases [8]. However, it has been observed that CNN models may not perform well with small datasets or when multiple diseases or viruses are present in the same image. Efforts have been made to address these limitations and improve the performance of CNN models in crop disease identification. This study explores the effectiveness of transfer learning algorithms and neural architecture search to identify multi-level crop disease, focusing on rust disease in Vicia faba crops. We aim to develop a real-time detection system that categorizes the disease into healthy, moderate, and critical levels. We assess their performance in accurately diagnosing crop rust disease by utilizing FCOS, Faster R-CNN, RetinaNet, and YOLO-family-family architectures. Our proposed architecture based on neural architecture search demonstrates significant advancements, particularly in precision, offering highly accurate diagnoses while minimizing false identifications.

2 Proposed method

2.1 Dataset collection, annotation, and preparation

The dataset used in this study for the Vicia faba L. rust disease originated from a farm in Ahfir, Berkane province, Morocco. A Sony DSLR-A230 camera was carefully placed between 30 and 50 cm away from the crop pods. In March and April of 2023, pictures were taken every three to four days, giving a thorough chronology of the disease's evolution. 3,296 Joint Photographic Group (JPG) photos in various orientations and angles make up the collection, which adds complexity. Three stages of exterior rust disease lesions on Vicia faba pods are depicted in the high-resolution, 3872x2592 pixel images: healthy, moderate, and critical. The dataset was divided into training, validation, and testing subsets using a 4:1:1 ratio. Images were resized to 640x640 while maintaining proportions to capture the evolution of rust disease. Accurate labeling was done using "LabelImg" and "MakeSense" tools in VOC format, generating XML and Txt files with precise annotations. These initiatives give farmers and researchers effective tools for controlling rust disease in Vicia faba L. crops [9].

2.2 A Novel Approach for Multi-Level Rust Disease Diagnosis

This study introduces a pioneering approach that utilizes neural architecture search-based image identification to diagnose multi-level rust disease in Vicia faba L. crops. By leveraging CNN for image analysis, our system accurately assesses disease extent and evaluates model efficacy [10]. It incorporates critical components like parameter configuration, data collection, pre-processing, annotation, and deep learning model training. This approach provides early warning information for efficient crop disease control, empowering farmers with improved decision-making and effective illness management strategies [11]. The system flow chart in Figure 1 outlines the recommended technique's process.

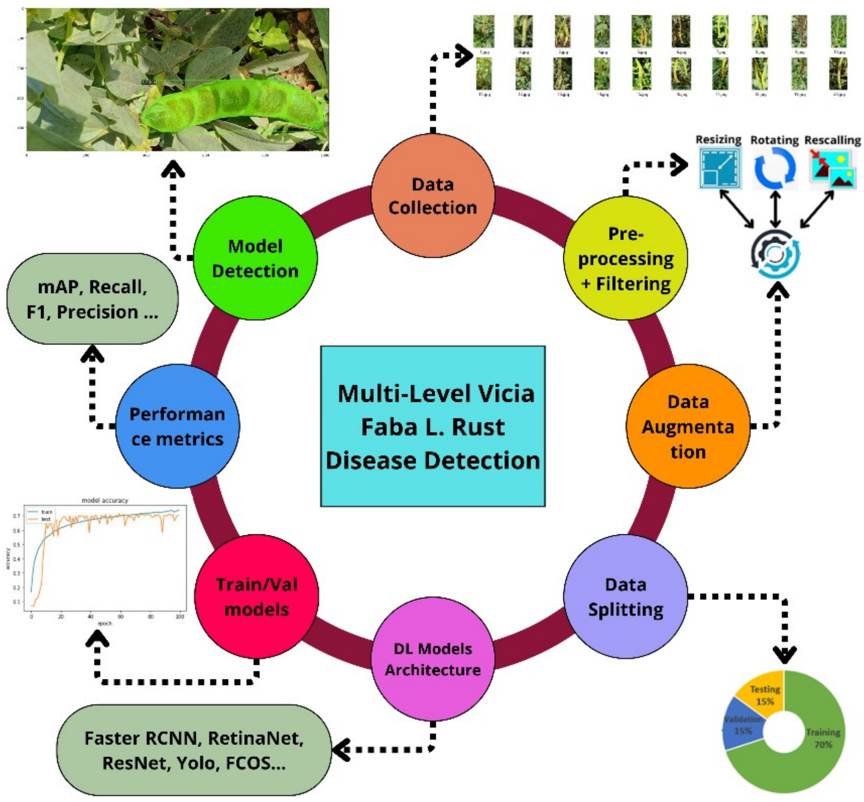

Fig. 1. Flowchart visualizing the proposed Deep Learning model.

2.3 Sequential steps in the proposed method

Our study uses transfer learning to expedite model construction and training. Pre-trained models such as Faster R-CNN ResNet, YOLO-Neural Architecture Search, RetinaNet ResNet, and FCOS are fine-tuned by modifying their architecture and adding new layers for improved performance. A dataset of 3296 images representing three infection levels is created specifically for this research, with photos resized to match the model's input layer requirements. The dataset is split into training, testing, and validation subsets (4:1:1 ratio), and a sequential layer-based architecture is designed to integrate the pre-trained models. Figure 2 illustrates the architecture of the proposed model.

Our study compares the trainable characteristics of different models for object detection, as shown in Figure 3. We evaluate their performance and complexity based on three metrics: Parameters, Weight, and FPS. Analyzing the number of parameters reveals insights into computational time and complexity. We find that models with more parameters require longer training due to increased complexity. This analysis helps understand the trade-off between model performance and training time, aiding in informed model selection.

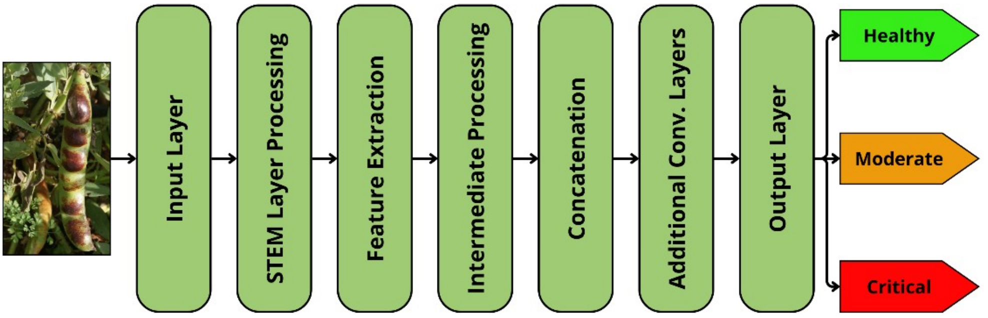

Fig. 2. YOLO-Neural Architecture Search model architecture.

2.4 Environment Setup

The project was developed using Python, and a computer in the electrical engineering department at the "Superior National School of Arts and Crafts (ENSAM)" in Rabat running Windows 10 was used to carry out the training work for this project and complete the multi-level detection of rust disease. Table 1 displays the server's particular setup for the experimental environment.

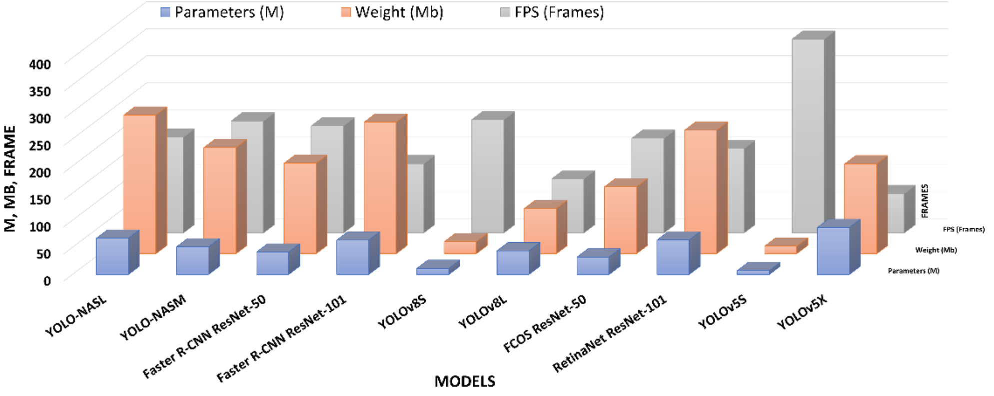

Fig. 3. Comparative assessment of trainable parameters, weight, and FPS in different models.

Table 1. Setup parameters for the experimental environment.

Configuration	Specific Version
Exploitation system	Windows 10 Professional
Programming language	Python v3.10.12
Deep learning framework	Torch v2.0.1
CUDA	V11.8
CPU	Intel® Xeon® W-2223 CPU 3.6 GHz
MEMORY	16 GB

GPU	NVIDIA GeForce Quadro P1000

3 Results and Discussion

We conducted a comprehensive comparative analysis of ten object detection models, including Faster R-CNN ResNet-101, YOLO-NASL, YOLO-NASM, Faster R-CNN ResNet-50, YOLOv8S, YOLOv8L, FCOS, RetinaNet ResNet-101, YOLO v5S, and YOLOv5X. The evaluation involved mAP, F1 Scores, Precision, and Recall. Specific details considered included the sizes of the training, validation, and test sets (2197, 824, and 275 images, respectively), optimization algorithms (Adam and SGD), learning rates ranging from 0.010 to 0.022, input image sizes of 640x640, batch sizes, and 50 epochs for training. These findings, summarized in Table 2, offer a detailed analysis of each model's training parameters and performance measures, providing valuable insights for informed model selection and evaluation in computer vision.

Table 2. Comparative evaluation of various trained models.

Degree of infection	Pretrained Models	P (%)	R (%)	mAP	F1 (%)	Speed (ms)
Healthy	YOLO-NASL	83,70	95,30	92,30	89,12	4,50
	YOLO-NASM	81,20	98,70	97,10	89,10	5,12
	Faster R-CNN ResNet-50	76,70	81,50	79,50	79,03	3,50
	Faster R-CNN ResNet-101	74,80	78,50	86,70	76,61	5,40
	YOLOv8S	90,30	91,10	94,70	90,70	3,60
	YOLOv8L	99,66	90,30	95,60	94,75	9,90
	FCOS ResNet-50	76,90	87,07	81,90	81,67	5,20
	RetinaNet ResNet-101	71,80	87,50	86,30	78,88	7,70
	YOLOv5S	75,30	70,30	77,70	72,71	1,90
	YOLOv5X	93,60	92,30	89,90	92,95	12,30
Moderate	YOLO-NASL	80,50	94,50	89,50	86,94	6,70
	YOLO-NASM	80,30	96,37	95,50	87,60	4,00
	Faster R-CNN ResNet-50	74,50	82,20	81,90	78,16	5,70
	Faster R-CNN ResNet-101	75,50	76,20	83,50	75,85	8,30
	YOLOv8S	89,50	89,50	89,50	89,50	6,10
	YOLOv8L	96,88	92,30	92,50	94,53	9,80
	FCOS ResNet-50	72,31	90,10	80,50	80,23	7,60
	RetinaNet ResNet-101	70,53	89,20	82,50	78,77	6,70
	YOLOv5S	74,50	67,50	72,50	70,83	3,40
	YOLOv5X	88,62	84,00	85,50	86,25	17,50
Critical	YOLO-NASL	81,90	94,60	91,10	87,79	5,90
	YOLO-NASM	93,40	96,40	89,99	94,88	4,72
	Faster R-CNN ResNet-50	75,30	84,10	84,70	79,46	6,00
	Faster R-CNN ResNet-101	72,10	84,90	86,30	77,98	9,76
	YOLOv8S	89,60	90,70	92,90	90,15	4,70
	YOLOv8L	87,10	87,74	93,60	87,42	10,70
	FCOS ResNet-50	78,00	89,80	83,70	83,49	4,39
	RetinaNet ResNet-101	80,10	82,30	87,70	81,19	4,92
	YOLOv5S	76,70	68,70	75,90	72,48	3,20
	YOLOv5X	85,60	90,30	92,70	87,89	11,60

The YOLO neural architecture search-based model for object detection demonstrates significant promise, showing substantial improvements over other models. Our proposed YOLO-NASM model achieves a notable 63.3% reduction in size compared to YOLO-

NASL, while still maintaining or enhancing performance. Compared to Faster R-CNN ResNet-101, YOLO-NASM shows a 19.1% reduction in size and is only 15.7% larger than YOLOv5X, highlighting its potential for improved performance. Specifically, YOLO-NASM achieves an 8.6% increase in precision, a 2.0% boost in recall, and an impressive 4.2% gain in mean Average Precision (mAP). These results underscore its efficiency and accuracy, particularly in resource-constrained scenarios, making it well-suited for real-time applications. However, despite these promising results, it is crucial to acknowledge and address the technical challenges associated with NAS and real-time implementation. Overcoming these challenges is essential to fully realize the potential of the YOLO-NASM approach in practical deployments. By focusing on optimizing computation efficiency and resource utilization, our approach aims to mitigate these obstacles, paving the way for broader adoption in real-time applications. Additionally, our trained model demonstrates its practical utility by accurately identifying rust disease levels on Vicia faba L. pods, effectively minimizing missed detections and false positives. This balance of model efficiency and high-performance positions YOLO-NASM as a robust solution for object detection tasks, even in demanding operational environments.

It excels at detecting small and numerous targets, making it a reliable tool for efficient disease management. Our analysis examines precision and recall functions used by our top-performing model for rust disease detection and classification. The study's results in Figure 4(a) show a precision value 1.00 within a 0.983 confidence interval, indicating an exact effect estimate. The importance of sufficient sample sizes and confidence intervals for accurate reporting and interpretation is emphasized. Figure 4(b) highlights the need for appropriate sample sizes and precise confidence intervals in understanding recall levels. Figure 4(c) reveals the relationship between recall, accuracy, and thresholds, emphasizing the correlation between high recall and low false negative rates and high accuracy and low false positive rates. The study achieved a mAP of 0.948, emphasizing the significance of large, reliable sample sizes, precise confidence intervals, and the connection between recall and precision for dependable and applicable results.

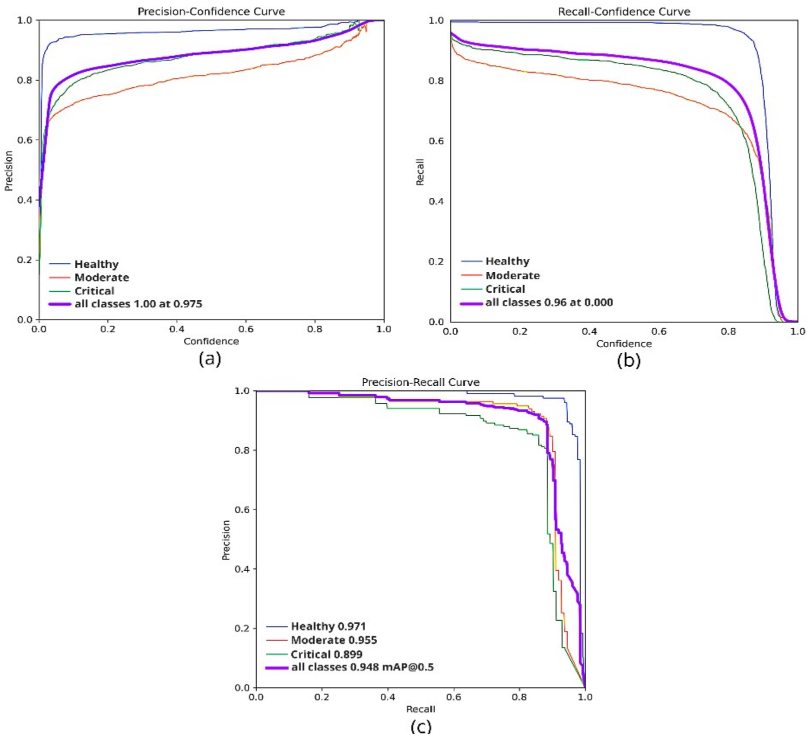

Fig. 4. Performance Analysis, (a) Precision-confidence curve, (b) Recall-confidence curve, and (c) Precision-Recall curve for multi-level Rust Disease Detection.

4 Conclusion

Our real-time multi-level rust detection experiments in Vicia faba L. crops revealed that the architecture YOLO based on the neural architecture search model outperformed other models. It displayed remarkable accuracy in identifying different illness classes, maintaining a high mean Average Precision (mAP) of 94.10%. The proposed model's adaptability is evident in its consistent performance across confidence thresholds, with a high mAP@50 score of 94.1%. It achieved an 84.8% precision rating, accurately recognizing true positives while reducing false positives. The model's robust recall rate of 96.96% further highlights its sensitivity in capturing many true positives. The final model demonstrates exceptional performance and suitability for precise and reliable disease diagnosis in various crops and complex agriculture. Its flexibility and potential for collaboration make it a valuable resource in the global fight against agricultural diseases, with significant implications for crop health and production optimization. Nevertheless, to fully unlock the benefits of the YOLO-NASM approach, it is essential to address the technical challenges associated with NAS and real-time implementation. By tackling these hurdles, future work can further refine the model's computational efficiency and responsiveness, facilitating its deployment in real-world applications.

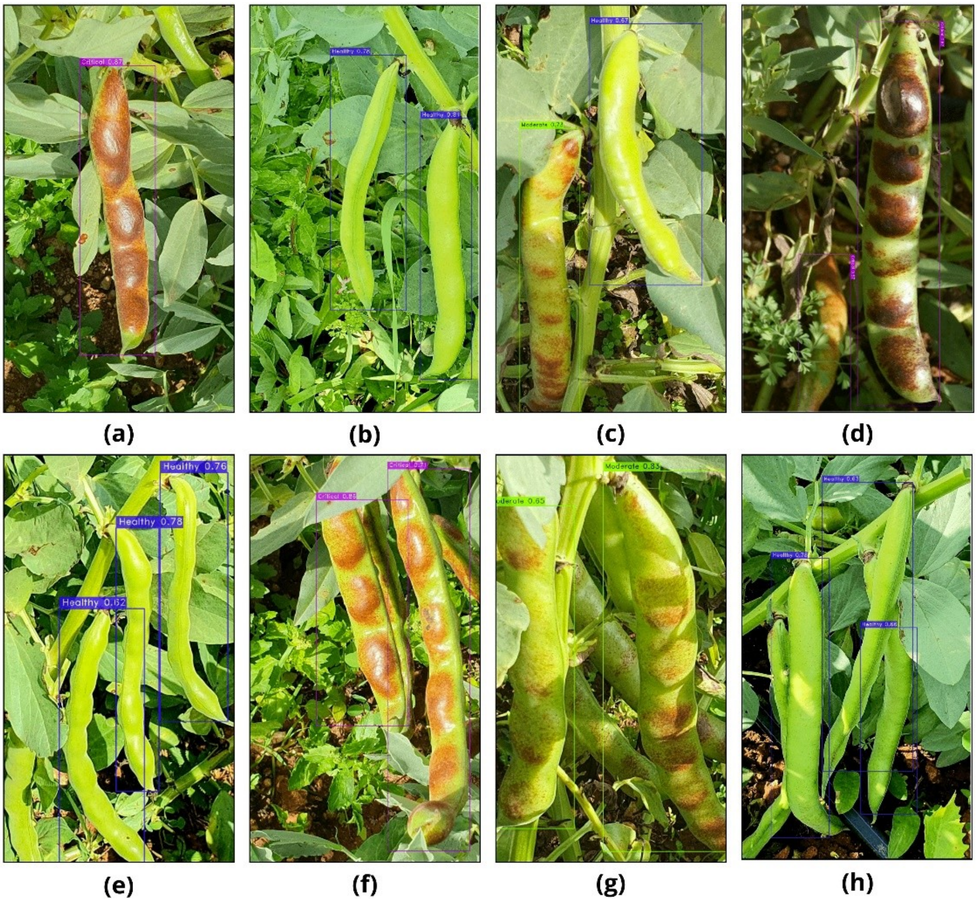

Fig. 5. Illustrative examples from the detection results of the YOLO model based on neural architecture search.

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