COMPARATIVE STUDY OF NEURAL NETWORKS FOR ENHANCED DETECTION OF *PHYTOPHTHORA INFESTANS* IN POTATO CROPS

Raluca TRUFELEA[1], Dan POPESCU[2]

Phytophthora infestans is the root cause of late blight in potato leaves. It is a devastating pathogen that leads to significant yield losses worldwide. It is crucial to detect the pathogen in early stages to prevent outbreaks and improve disease management strategies. This study compares YOLO architectures, starting from YOLOv7 to YOLO12, tailored for high-accuracy detection of Phytophthora infestans. The database consists of images from healthy leaves to early blight leaves, to late-blighted leaves, in potato crops, being publicly available. Experimental results show that YOLO12n achieved the highest precision of 0.999, outperforming all the other models. The proposed article contributes to precision agriculture by providing an automated, scalable, efficient integrated pathogen management detection system.

Keywords: *Phytophthora infestans*, YOLO, Potato Crops, Deep Learning, Agriculture, Computer Vision

1. Introduction

Phytophthora infestans is a fungal pathogen responsible for late blight disease. This devastating disease is affecting potato and tomato crops. Experts [1] consider it to be one of the most aggressive plant pathogens, due to its fast spreading and destructive impact on global agriculture. The infection primarily targets leaves, but it also affects stems and tubers. As a representative of the Stramenopila family, P. Infestans is phylogenetically closer to algae than fungi and shows a complex life cycle. It diffuses predominantly through air and water under high humidity and moderate temperature conditions.

Phytophthora infestans is a fungal-like oomycete pathogen responsible for the disease commonly known as "potato late blight," widely regarded by experts as the most aggressive plant pathogen. This microorganism primarily affects potato and tomato crops, causing significant damage to the leaves, stems, and tubers.

The disease is highly destructive, leading to substantial losses both globally and nationally in the agricultural sector.

[1] Eng., National University of Science and Technology POLITEHNICA Bucharest, Romania, e-mail: raluca.trufelea@stud.acs.upb.ro

[2] Prof., Dept. of Automation and Industrial Informatics National University of Science and Technology POLITEHNICA Bucharest, Romania, e-mail: dan.popescu@upb.ro

Phytophthora infestans belongs to the kingdom *Stramenopila*, making it more closely related to algae than fungi, and it has a complex life cycle. It spreads primarily through airborne and waterborne spores, thriving in high humidity and moderate temperatures. This fungal infection produces sporangia and zoospores, which could germinate in water and rapidly infect host plants.

Constant monitoring of agricultural pests enables specialists to assess infestation levels and develop effective pest management strategies. This study investigates the capability of convolutional neural networks in classifying the degree of infestation in potato crops. It explores the detection of three infestation stages: healthy plants, an intermediate stage with moderate infestation, and the final stage of severe infection. Top accurately find damage caused by *Phytophthora infestans*, a decision fusion system including multiple neural networks was employed.

The control of *Phytophthora infestans* is a highly labor-intensive process, requiring significant time and resources. One common method is crop's rotation, which prevents the planting of tomatoes near potato fields and restricts the reuse of the same land for these crops in consecutive years, thereby reducing the favorable conditions for fungal proliferation. Another often used strategy involves cultivating *Phytophthora infestans*-resistant plant varieties, although resistance is not entirely foolproof. Additionally, removing infected plants from fields serves as an important measure to halt the spread of the pathogen.

Managing the spread of this infection is complex but possible. Both chemical and biological control methods are employed. Chemical control involves the systematic application of preventive fungicides, often in varying formulations, as *Phytophthora infestans* can develop resistance to fungicidal treatments. Biological control methods relieve bacteria such as *Pseudomonas fluorescens* and *Bacillus subtilis*, as proved by scientific studies.

The focus on *Phytophthora infestans* in this research stems from the severe economic damage it has caused both historically and in the present. This pathogen was notoriously responsible for triggering the Irish Potato Famine (1845–1852), which led to widespread human losses and increased migration rates. Today, this fungal infection continues to inflict substantial economic damage, particularly in regions where potato and tomato cultivation is a primary source of income. Consequently, this study aims to mitigate such losses through early infestation detection, improved classification performance, and scalable analysis methods, all of which contribute to cost reduction.

A modern solution in plant disease management is artificial intelligence (AI). AI plays a crucial role in agriculture, aiding in the identification of various plant species and agricultural pests, including potato late blight caused by *Phytophthora infestans*. AI can detect early symptoms of plant diseases far more efficiently than the human eye. Essential components in this context include imaging devices such as cameras, drones, surveillance systems, and integrated field sensors, which prove continuous monitoring systems that detect subtle changes before they become visible to human observers. This enables prompt intervention to prevent disease spread, reduce costs, and minimize material losses caused by pests.

AI also plays a key role in predicting environmental conditions that favor plant diseases. It allows for the analysis of meteorological data, humidity levels, temperature fluctuations, and other environmental factors that contribute to pathogen dissemination. By using such information, farmers receive real-time alerts regarding environmental changes and pathogen progression. Additionally, recommendation systems can provide personalized guidance, enabling prompt action to mitigate potential risks.

Artificial Intelligence revolutionized plant disease management by enabling rapid and precise pathogen detection. This approach facilitates early intervention, reducing economic losses, mitigating disease spreading, and supporting agricultural development. This study contributes to the development of scalable, cost-effective solutions for safeguarding global food security by integrating AI-driven disease detection with precision agriculture.

This paper presents the training and testing methodologies for the YOLO family to detect *Phytophthora infestans* in potato crops. The Experimental Results section discusses the strategies adopted in developing the application and compares the performances of different networks to determine the most effective network as a recommendation for end users. Finally, the *Discussions* and *Conclusions* sections provide a comprehensive analysis of the findings and insights drawn from this research.

2. Related works

Researchers propose an automated identification method based on VGG19 for potato leaf detection [2]. This approach leverages computer vision to detect four common diseases: bacterial spots, early blight, late blight, and mite damage. The VGG19 model was fine-tuned using transfer learning on this dataset, achieving an impressive accuracy of 95.2% on the test set, outperforming other state-of-the-art methods. Early identification and classification of seven common potato diseases, including early blight, late blight, and other leaf diseases, was also the focus of study [3]. The proposed model employs deep learning techniques and is built upon a complex CNN architecture comprising three convolutional layers, three max-pooling layers, and two fully connected layers. The model's purpose is to enable more accurate and early disease detection, providing farmers and agricultural specialists with effective tools for disease management and improved crop protection.

Paper [4] proposes using CNNs to automate the detection process, enabling the early identification of potato leaf diseases. This study utilizes the "Potato Disease PyTorch Lightning CNN" dataset from Kaggle, similarly to the present research, for training the CNN model. The model achieved an impressive disease classification accuracy of approximately 98.6%.

The evaluation of a total of eight deep learning (DL) models, including both custom-built and pre-trained architectures, using two validated datasets. The compared models include ResNet50, VGG16, a hybrid CNN-KNN, VGG19, SBCNN, InceptionV3, AlexNet, and a hybrid CNN-SVM [5]. Among these, the study found that ResNet50 achieved the highest accuracy in detecting potato leaf diseases, particularly CNN-based models, in enhancing the precision and efficiency of disease detection in potato crops. This achievement could play a crucial role in enabling prompt inventions and minimizing crop losses.

Potato leaf images were categorized into three classes: healthy leaves, leaves affected by early blight, and leaves affected by late blight. A crucial aspect of the researcher [6] was balancing the dataset using oversampling techniques to prevent class imbalance. The data was then processed using a Convolution Neural Network (CNN), which employs multiple processing layers to extract and identify essential features from the images. The methodology involved selecting the optimal activation function, optimizer, the ReLU activation function, and 250 epochs. This result proves significant potential for the fast and precise diagnosis of potato leaf diseases, aiding farmers and agricultural authorities in implementing effective preventive measures.The primary diseases examined in [13] include late blight, early blight, and another leaf disease, all of which cause significant economic and ecological losses for farmers. The research aims to enable early detection of these diseases to minimize losses and safeguard the value of agricultural production. The study employs four categories of disease-affected leaves and one category of healthy leaves and evaluates three deep learning models: VGGNet16, ResNet101, and a modified version of AlexNet. The modified AlexNet model yielded the best results, achieving 99.97% accuracy during training and 61% accuracy in testing. This automated disease detection system has the potential to become a valuable tool for farmers, facilitating rapid diagnosis and effective intervention to prevent crop losses. This capability can significantly reduce the time and costs associated with manual crop health assessment.

3. Materials and methods

3.1. Database used

The dataset "Potato Leafe Disease Gallery" is a public database available on Kaggle, being a valuable resource for researchers. This holds labeled images of early, late blight, and healthy leaves. The images are captured from different angles and lighting conditions, creating various datasets suitable for training computer vision models.

Each image is annotated with a specific disease type or marked as healthy for unaffected leaves. This structured labeling enables the training of models capable of distinguishing between healthy and infected leaves, including crop health monitoring, where fast disease detection allows farmers to take prompt action, thereby minimizing the risk of yield loss. Additionally, it plays a crucial role in precision agriculture, using advanced technologies to monitor and safeguard crops, ultimately enhancing agricultural efficiency and sustainability. In Table 1, the overview of the database is presented, explaining how balanced the number of images and the number of classes are.

Table 1

Database overview

Class	Number of Images
Healthy leaves	152
Early blight leaves	1000
Late blight leaves	1000
Total	2152

As it can be seen in Table 1, the dataset is not balanced. In that regard, the class Healthy leaves were augmented to increase the size of the dataset from 152 to 1000, as with the other classes, counting 3000 images in total. Table 2 also reflects the database after augmentation. The augmentation techniques used for the Healthy leaves class were horizontal flip, rotation, scale, vertical flip, brightness contrast, Gaussian blur, padding, and crop. For training/ validation, 800/ 200 images were used, as seen in Table 2.

Table 2

Database overview after image augmentation

Class	Number of Images for Training	Number of Images for Validation
Healthy leaves	800	200
Early blight leaves	800	200
Late blight leaves	800	200
Total	2400	600

The dataset is frequently employed with deep learning algorithms, particularly CNNs, which can analyze images, extract intricate features, and learn to recognize disease based on visual patterns. Before training models, data preprocessing is essential and typically involves noise reduction and image augmentation. Noise reduction improves image quality by removing artifacts, while augmentation through transformations such as rotation, scaling, and brightness adjustment enhances dataset diversity, helping prevent model overfitting. Figure 1 illustrates a representative example of each available class.

Fig. 1. a) Early_blight_leaves, b) Healthy_leaves, c) Late_blight_leaves

3.2. Neural Networks Used

The YOLO models, starting with YOLOv7 until YOLO12, were trained and proved progressive improvements in detection accuracy and efficiency, which highlighted the benefits of leveraging the latest advancements in object detection architectures. This approach shows performance improvements in accuracy, speed, and offering valuable insights into the evolution of the YOLO family architecture.

YOLOv7 is a real-time object detection model that redefines the benchmarks for speed and accuracy in computer vision. It is particularly well-suited for applications such as object tracking, autonomous driving, robotics, and medical image analysis. One of the defining characteristics of this architecture is its performance, optimized for a broad range of frame rates, spanning from 5 FPS to 160 FPS. With an average precision (AP) of 56.8%, YOLOv7 [7] stands as the most accurate real-time object detector for applications demanding speeds above 30 FPS. Among its notable innovations in design and training, YOLOv7 employs model reparameterization, which enhances performance by improving gradient flow within the network architecture. It also introduces a guided label assignment system, specifically fine-tuned for networks with multiple output layers. In Fig. 2, the architecture of YOLOv7 is presented.

YOLOv8 is one of the latest iterations in the YOLO series, developed by Ultralytics, marking a significant advancement in real-time object detection. This version integrates cutting-edge features and optimizations, making it well-suited for a diverse range of applications, from object detection to more complex tasks such as segmentation, key point detection, and classification.

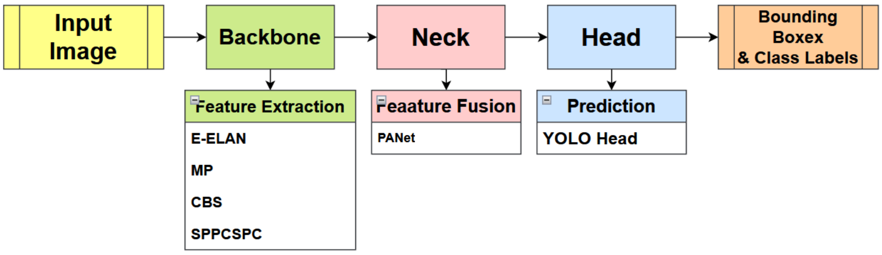

Fig. 2. YOLOv7 architecture

The available YOLOv8 models start with YOLOv8n and end with YOLOv8x. The difference consists of the number of parameters used and the FLOPs. Key advantages of YOLOv8 [8] include its superior performance, as it surpasses earlier versions in both accuracy and speed. Its architecture is highly versatile, designed to excel not only in object detection but also in segmentation, classification, and other sophisticated tasks. In Fig. 3, the architecture of YOLOv8 is shown.

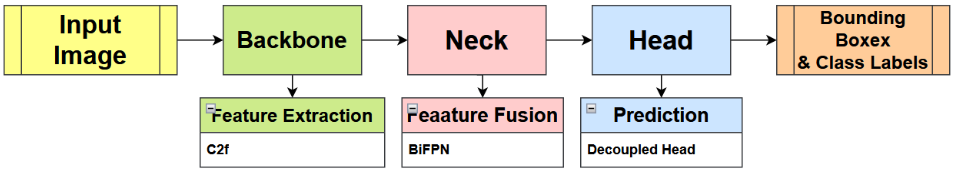

Fig. 3. YOLOv8 architecture

YOLOv9 [9] has introduced significant advancements in real-time object detection, particularly on the COCO dataset, setting new benchmarks for efficiency and accuracy. Its various model variants, ranging from tiny (t) lightweight versions to large-scale (e) models, prove notable improvements in mean Average Precision (mAP) while significantly reducing computational demands and parameter counts. This makes YOLOv9 not only more precise but also more efficient than its predecessors and competing models. These improvements solidify YOLOv9's position as object detection model, excelling in both accuracy and resource optimization. In Fig. 4, the architecture of YOLOv9 is presented.

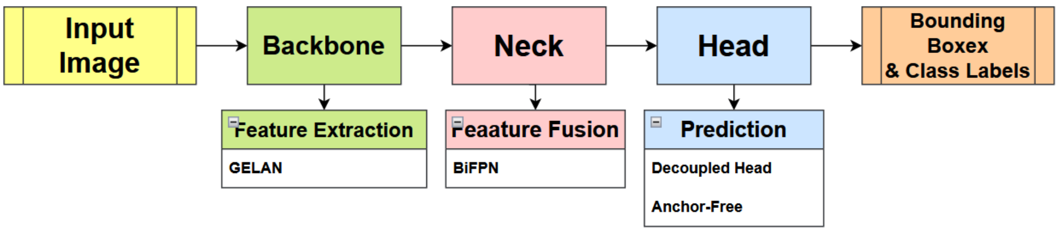

Fig. 4. YOLOv9 architecture

YOLOv10 [10], released in 2024, introduces a series of enhancements that make it faster and more efficient, continuing YOLO's tradition of prioritizing real-time performance. Key features of YOLOv10 are reducing the parameter count and lowering the latency. Also, the refined architecture for improved computational efficiency, the Non-Maximum Suppression (NMS)-free approach, and consistent dual assignments for better object detection accuracy. YOLOv10 is specifically designed to minimize the number of parameters required for detection, leading to lower latency and reduced hardware resource consumption. The difference consists of the number of parameters used and the FLOPs. For instance, YOLOv10-B features 25% fewer parameters compared to YOLOv9-C and achieves 46% lower latency, making it an ideal choice for real-time applications on resource-constrained devices, such as drones and security cameras. In Fig. 5, the architecture of YOLOv10 is presented.

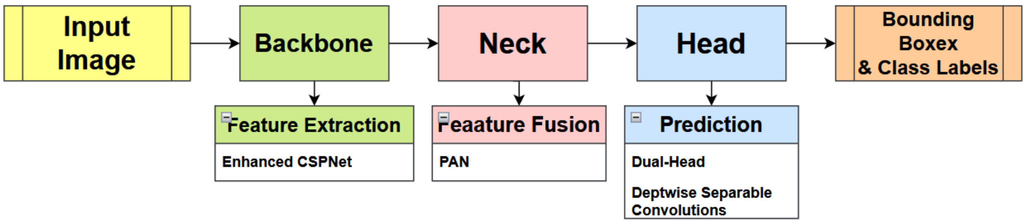

Fig. 5. YOLOv10 architecture

YOLO11 [11], also released in 2024, stands for the pinnacle of YOLO's evolution, incorporating the most advanced techniques in computer vision and machine learning. This makes it a top-tier choice for any application requiring high-quality real-time object detection. Key Features of YOLO11 are enhanced architecture with advanced feature extraction techniques, expanded scope for various computer vision tasks and optimized processing speeds for even faster performance. YOLO11 introduces 5 new models, starting from YOLO11n to YOLO11x.

YOLO11 introduces significant architectural improvements, enhancing its ability to capture fine details in complex images. It can detect not only standard objects but also subtle objects or those in challenging lighting conditions. Beyond object detection, YOLO11 now supports instance segmentation, enabling the identification of individual objects within an image, pose estimation, allowing for spatial understanding of an objects or person's position, and oriented object detection, capable of recognizing objects at unusual angles. With these advancements, YOLO11 sets a new benchmark for precision, versatility, and efficiency in real-time computer vision applications. In Fig. 6, the architecture of YOLO11 is presented.

YOLO12 [12] introduces an Area Attention Mechanism, a novel self-attention approach that efficiently handles large receptive fields by dividing feature maps into equal-sized regions, significantly reducing computational costs.

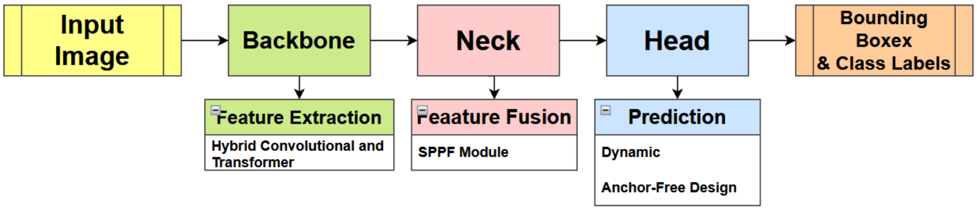

Fig. 6. YOLO11 architecture

It also features Residual Efficient Layer Aggregation Networks (R-ELAN), an improved aggregation module with block-level residual connections and a bottleneck-like structure for enhanced optimization.

The model streamlines standard attention mechanisms using FlashAttention, removing positional encoding, adjusting MLP ratios, and incorporating a 7×7 separable convolution to implicitly encode positional information. As well as the previous models, YOLO12 introduces 5 new models, from YOLO12n to YOLO12x.

YOLO12 is designed for versatile computer vision tasks, including object detection, instance segmentation, classification, pose estimation, and oriented object detection. It achieves a strong balance between speed and accuracy by reducing parameters while supporting high performance. It enhanced feature extraction, optimization stability, and architectural efficiency, being suitable for various applications. In Fig. 7, the model architecture of YOLO12 is presented.

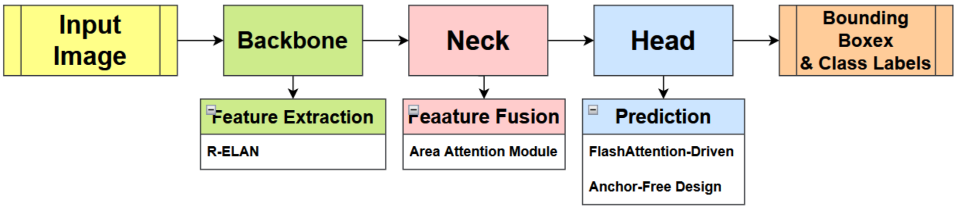

Fig.7. – YOLO12 architecture

The models were evaluated using the key performance metrics, presented in Tabel 3, such Precision (P), Recall (R) and Mean Average Precision (mAP) to assess their accuracy and effectiveness in the classification task.

Table 3

Performance Metrics

Name	Formula	Parameters
Precision	$P = \frac{TP}{TP + FP}$	TP = True Positive, FP = False Positive values
Recall	$R = \frac{TP}{TP + FN}$	TP = True Positive, FN = False Negative values

Mean Average Precision	$mAP = \frac{1}{n} \cdot \sum_{k=1}^{k=n} APk$	n = total number of classes, k = the index of a specific class, APk = sum of the Average Precision (AP) values across all n classes

Precision measures the proportion of correctly identified instances out of all predicted instances, while Recall reflects the model's ability to detect all relevant instances within the dataset. Mean average precision (mAP) provides a comprehensive evaluation by combining both precision and recall, across different confidence thresholds.

4. Results

The system diagram, presented in Figure 11, illustrates a standard machine learning pipeline, broken into four main stages as it follows: data acquisition, data preprocessing, modelling, result evaluation. Data acquisition involves collecting raw data from various sources such sensors or cameras, public or proprietary databases, manual annotation or scraping. The purpose of it is to to gather sufficient and relevant data that will serve as the foundation for the entire modeling process. Once data is collected, it must be cleaned and transformed. This stage, data preprocessing includes removing noise, duplicates, or irrelevant features, normalization or standardization, data augmentation and splitting into training, validation, and test sets the purpose of it is to prepare the data in a format suitable for training a model while reducing bias and improving performance. The modelling step focuses on building the machine learning or deep learning model choosing the model architecture, training the model on preprocessed data and tuning hyperparameters to optimize performance, with the purpose of learning patterns or relationships within the data to make predictions or classifications. Finally, the trained model is assessed using metrics such as accuracy, precision, recall, F1-score. Since the input involves static images, inference time is not critical here, meaning evaluation focuses more on model accuracy and generalization rather than speed.

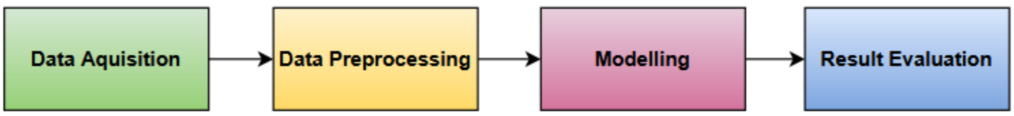

Fig. 11. – System diagram

The models were trained using a cloud virtual machine powered by a GPU PNY NVIDIA TESLA T4 TCST4M-PB and CUDA 12.4 toolkit. The training for the YOLO models was performed the same, with batch dimensions of 16 on 100 epochs, with a 640x640 image dimension. While training, callbacks were defined as checkpoints for saving only the best weights, early stopping, and reducing the learning rate. Table 4 presents the leaves diseases studied in this paper, the number of images per class used for training, and for validation. Due to the small size of the dataset, it led to overfitting, as the model learned the training data too well but failed to generalize to unseen examples.

Table 4

Classes overview

Class	Class name	Total Number of Images	Number of Images for Training	Number of Images for Validation
Healthy leaves	Healthy_leaves	1000	800	200
Early blight leaves	Early_blight_leaves	1000	800	200
Late blight leaves	Late_blight_leaves	1000	800	200
Total		3000	2400	600

In Table 5, the results obtained on the training phase are presented, and in Table 6 the results obtained in the validation phase are shown.

Table 5

Training results

Architecture	Precision	Recall	mAP50	mAP95	Inference (ms)
YOLOv7	0.574	0.733	0.666	0.466	14.3
YOLOv8n	0.975	1	0.993	0.978	2.0
YOLOv9n	0.976	0.991	0.993	0.983	1.3
YOLOv10n	0.946	0.977	0.994	0.959	3.09
YOLOv11n	0.998	1	0.995	0.988	2.7
YOLOv8m	0.997	1	0.995	0.961	9.95
YOLOv9m	0.969	0.992	0.991	0.99	12.56
YOLOv10m	0.988	0.987	0.994	0.954	11.24
YOLO11m	0.978	0.996	0.994	0.965	11.4
YOLO12n	0.999	0.999	0.995	0.982	4.2
YOLO12m	0.999	1	0.995	0.991	3.5

Table 6

Validation results

Architecture	Precision	Recall	mAP50	mAP95	Inference (ms)
YOLOv7	0.574	0.733	0.666	0.466	14.8
YOLOv8n	0.975	1	0.993	0.98	3.8
YOLOv9n	0.976	0.991	0.993	0.983	2.3
YOLOv10n	0.939	0.987	0.995	0.96	5.8
YOLOv11n	0.998	1	0.995	0.988	4.7
YOLOv8m	0.997	0.999	0.995	0.962	24.6
YOLOv9m	0.969	0.992	0.991	0.99	25.2
YOLOv10m	0.987	0.987	0.995	0.995	12.2

YOLO11m	0.978	0.996	0.994	0.965	26.9
YOLO12n	0.999	0.999	0.995	0.984	6.2
YOLO12m	0.999	1	0.995	0.991	5.6

As it can be seen, the YOLO11m model obtained the best mAP95, 0.995. The best mAP50 is 0.995, obtained by several models as YOLOv10n, YOLO11n, YOLOv10m, and YOLO12n. The best recall score, 1, is obtained by YOLOv8n and YOLO11n. The most precise model is YOLO12n, which obtained 0.999. On the other hand, YOLOv7 obtained the lowest results in this task. Since the inference involves a comparison of static images, the time factor is not critical or relevant in this context.

In Fig. 12**,** experimental results from all the classes in the training and validation phases are displayed.

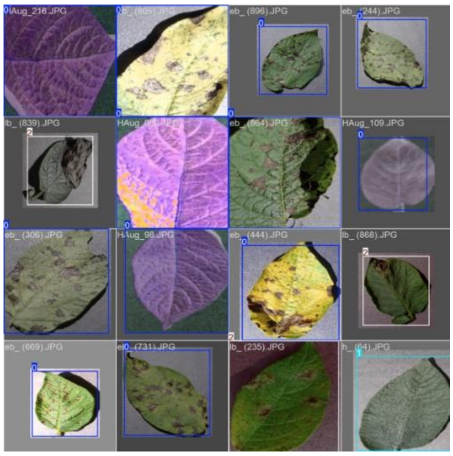

Fig. 12. – Experimental results from all the classes

Table 7

Class annotations

Class	Class annotation	Name of the Image
Early blight leaves	0	Starts with e/E
Healthy leaves	1	Starts with h/H
Late blight leaves	2	Starts with l/L

Analyzing Fig. 12 and Table 7, there are both correctly classified and misclassified images. For example, Image 'Haug_216.JPG' is part of the healthy leaves class, but it was classified as an early blight leaf, while 'h_ (64).JPG' was correctly classified.

5. Conclusion

In this study, the authors explored the effectiveness of YOLO object detection models from YOLOv7 to YOLOv12 for the detection of potato leaf infestation in precision agriculture. Across all versions, the models proved strong performance in accurately finding signs of infestation under diverse field conditions. Importantly, the authors have shown that YOLO's real-time processing capabilities, particularly in its recent versions, make it ideal for field deployment in precision agriculture, where prompt identification of crop diseases is crucial for minimizing yield loss. These findings underscore the suitability of YOLO-based models as practical tools for supporting early intervention and automated crop monitoring in real-world agricultural settings.

In conclusion, deep learning architectures, particularly convolutional neural networks (CNNs), have proven to be highly effective in the agricultural domain, especially in the detection and management of plant diseases such as *Phytophthora infestans*. These architectures enable precise image classification, disease detection, and early identification of affected areas, which is crucial for improving crop yields and reducing the need for chemical interventions. In agriculture, CNN-based models, including popular architectures like YOLO (You Only Look Once), are used to analyze images of plants and detect symptoms of diseases, enabling farmers to take timely actions to prevent widespread infection. YOLO is known for its real-time processing capabilities, which make it ideal for field deployment in precision agriculture. Furthermore, advancements in architecture, like YOLOv7 and others that focus on transfer learning, have significantly reduced the amount of labeled data needed for training models, making them more accessible and effective in various agricultural settings. The application of these architectures in the context of *Phytophthora infestans* provides a powerful tool for early detection, monitoring, and management, which not only supports sustainable farming practices but also contributes to better food security by mitigating crop losses caused by this devastating pathogen.

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