ISSN: 2584-0495 Vol. 2, Issue 1, pp. 492- 499

International Journal of Microsystems and IoT

ISSN: (Online) Journal homepage: https://www.ijmit.org

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Cite as: HAZRA, S., KARFORMA, S., CHAKRABORTY, D., CHAKRABORTY, S., & HALDAR, S. (2024). Potato Leaf Disease Detection Using YOLOv8n with a Handheld Device. In International Journal of Microsystems and IoT (Vol. 2, Number 1, pp. 492–499). Zenodo. https://doi.org/10.5281/zenodo.10700359

Published online: 22 January 2024

DOI: https://doi.org/10.5281/zenodo.10700359

International Journal of Microsystems and IoT
Vol. 2, Issue 1, pp. 492- 499; DOI: https://doi.org/10.5281/zenodo.10700359

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Potato Leaf Disease Detection Using YOLOv8n with a Handheld Device

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ABSTRACT

This study addresses the urgent need for timely detection of leaf diseases in agriculture to mitigate potential crop losses and subsequent negative impacts on the global economy. We propose a deep learning-based technique for potato leaf disease recognition, utilizing the Ultralytics YOLOv8n model trained on PlantVillage datasets, with the aim of enabling detection using handheld devices like mobile phones or Internet of Things (IoT) devices. Evaluation metrics including precision, recall, F1-score, mean Average Precision (mAP) at different Intersection Over Union (IOU) thresholds demonstrate the robust performance of the model, with high values across all metrics, such as precision (94.57%), recall (94.164%), F1-score (97.297%), and mAP (94.367%). These outcomes underscore the efficacy of the YOLOv8n model in accurately finding diseased regions within potato leaves. The potential applications of this approach extend beyond disease detection alone, with implications for precision farming and crop management. Overall, this research contributes to advancing technologies aimed at improving agricultural productivity, resilience, and economic sustainability through efficient disease management strategies.

KEYWORDS
Computer Vision, Deep learning, Image Classification, Object Detection, Plant leaf disease detection, Precision Agriculture, YOLOv8n.

1. INTRODUCTION

A lot of developing countries rely heavily on agriculture as their main economic driver. The notable increase in food production has been instrumental in enabling the growth of the world population throughout the 21st century. Hence, employing machine learning (ML) algorithms to precisely forecast healthy crop yields or crop types emerges as a pivotal concern in agricultural advancement [1]. The development of agricultural products depends on pesticides. Farmers have employed them to manage insects and weeds, and it is said that they have made a substantial contribution to higher agricultural productivity [2].

However, there is a serious risk to agricultural productivity from the spread of plant diseases. An increase in food insecurity may result from a delayed identification of certain illnesses [3]. Early identification is essential for the effective prevention and control of illnesses and is a key component in agricultural production management and decision-making. In recent times, there has been a growing urgency to identify these illnesses. Usually, the leaves, flowers, fruits, or stems of the affected plants have lesions or markings on them; each disease has a characteristic pattern that helps with identification. Plant illnesses are typically first symptomatic in the leaves, hence these are frequently the main signs of the disease. Recent developments in computer vision have made it feasible to promptly recognize and address these issues [4].

Numerous techniques have been developed by the scientific community to diagnose and classify plant diseases. Traditional methods of processing images still exist, involving the manual extraction and segmentation of features. Even with the promise of these methods, disease detection is still a labor- and time-intensive procedure [5]. Moreover, models that depend on spot segmentation and classification require human involvement. The progression of artificial intelligence has resulted in the utilization of deep learning and ML models to improve the accuracy of computer vision recognition [6]. With the use of these techniques, feature extraction and automatic categorization have improved and can now correctly represent the original image features. The shift from classical methods to deep-learning platforms has been made easier by the availability of datasets, GPU processors, TPU processors, and software. This has allowed complex deep-learning architectures to be created with less complexity. The capacity of convolutional neural networks (CNNs) to extract low-level complicated characteristics from images has attracted a lot of attention since it significantly improves detection and classification capabilities [7].

Plant leaf diseases are difficult for deep neural networks to detect in natural environments because of dense foliage, large-scale modifications, and complicated backgrounds. Comparing one-stage algorithms to other deep learning models, they have proven to perform better [8]. Recent advances in deep learning-based image identification networks set two-stage and single-stage image identification networks apart. Regional ideas are intended for two-stage networks, including the SPPNet, Region-based CNN algorithms family (Mask R-CNN, Faster R-CNN, Fast R-CNN, R-CNN, etc.). Conversely, single-stage algorithms are best represented by the SSD from the YOLO series [9].

The method of object detection known as "You Only Look Once," or YOLO, is utilized for this purpose. 2015 saw the release of YOLOv1, the program's initial iteration [10]. For YOLO to operate, the image is partitioned into a grid of equally sized cells with dimensions $m \times m$. If an object's center is inside a cell, then that cell is in charge of recognizing the object. Furthermore, a fixed number of bounding boxes can be predicted by each cell, and each forecast comes with a confidence score. Five values make up these predictions: x, y, w, h, and a confidence level, where, 'w' represents the width, 'h' represents the height, and 'x' and 'y' denote the central point of the enclosing box.

When bounding boxes are predicted, YOLO uses an approach known as Intersection Over Union (IOU) to determine which bounding box within a grid cell is the most accurate for a given object. Then, Non-Maximum Suppression is applied to get rid of unnecessary bounding boxes. Following the first release of YOLO, YOLOv2 and YOLOv3 were released in 2016 and 2017, correspondingly [11]. YOLOv4 was later unveiled by Alexey Bochkovskiy in 2020 [12]. Following YOLOv4, Glenn Jocher created YOLOv5 [13], which is entirely constructed using the PyTorch framework. The detection models for YOLOv6 [14] and YOLOv7 [15] were made available in June and July of 2022, respectively. Finally, in January 2023, Ultralytics published YOLOv8 [16].

Several research studies have concentrated on detecting diseases in potato leaves. In [17], the authors devised a model based on image segmentation employing SVM for potato leaf detection, utilizing the PlantVillage dataset, and attained a 95% accuracy. Similarly, the authors in [18] introduced a hybrid technique for identifying diseases in apples, incorporating image segmentation through k-means clustering followed by classification using the random forest algorithm. They reported accuracy of their model ranging from 60 to 100%. The authors in [19] employed the PlantVillage dataset to identify early blight in potato within a real-time system using VGGNet, GoogleNet, and EfficientNet. They obtained best accuracy of 99% employing EfficientNet. VGG16 is suggested in [20] as a more effective model for detecting early late blight leaf diseases of potato. They evaluated VGG16, VGG19, MobileNet, and ResNet50 using the PlantVillage dataset, with VGG16 yielding superior results after fine-tuning. Their approach resulted in an accuracy of approximately 97.89% in classifying between the two disease classes. In another notable study [21], the author introduced a MobileNet model for detecting potato leaf diseases. The lightweight MobileNet V2 achieved a high accuracy of 97.73% in predicting potato leaf diseases.

In this investigation, YOLOv8 models for detecting potato leaf disease in several agricultural field settings were evaluated.

A pivotal moment in the evolution of artificial intelligence for object detection is marked by the emergence of the YOLO neural network. Real-time image processing is made possible by its remarkable inference speed, which makes it ideal for a variety of applications like augmented reality, robotics, video surveillance, self-driving cars, road fracture detection, and precision agriculture. Ultralytics' most recent version, YOLOv8, brings many improvements over earlier iterations. The features of YOLOv8 go beyond those of the original YOLO and include image categorization, object identification, and instance segmentation. These tools give farmers a way to quickly detect plant illnesses and suggest preventative actions to reduce losses in crop yield.

In this study, we employ the Ultralytics YOLOv8n model for object detection. We trained this model using a dataset compiled from images sourced from the PlantVillage dataset. Our results showcase the effectiveness of training the YOLOv8n model from the ground up, validating its performance on a dataset of plant leaf diseases. This highlights the potential of leveraging the advanced object detection capabilities offered by YOLOv8n to address the significant challenge of identifying plant diseases. To the best of our knowledge, YOLOv8n's application in plant disease detection has not been investigated in previous study.

2. METHODOLOGY FRAMEWORK

The methodology framed in this work comprises four key steps: acquisition of data, preprocessing of data, training, and evaluation, which collectively guide the execution of this study. The process flow diagram using YOLOv8n model for potato plant leaf disease detection presented in Fig. 1. is described as follows. First, the information is gathered and preprocessed using a variety of methods including image extraction, labeling, augmentation, and resizing of data. The dataset is then partitioned into sets for training, validation, and testing. The YOLOv8n model is then thoroughly tested to assess its performance after being trained from scratch.

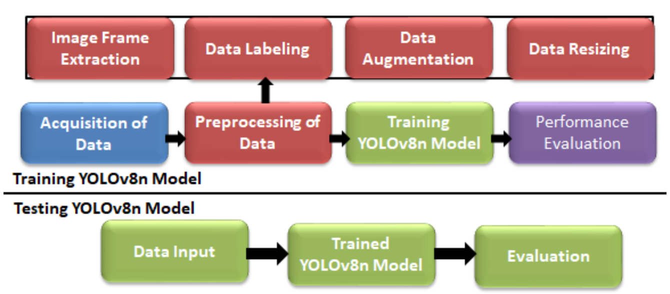

Fig.1 Procedure for developing and implementing a YOLOv8n-based classification and localization of potato leaf disease model.

A. Acquisition of Data

The popular online dataset PlantVillage is downloaded from https://www.kaggle.com/datasets/emmarex/plantdisease for the study. The dataset contains [22] 20,639 photos from the PlantVillage collection show three different crop species: pepper, tomato, and potato. These meticulously chosen photos from the internet depict both healthy and unhealthy crop leaves. We intentionally choose pictures of potato leaves for our investigation. After gathering these photos, we adjusted the leaf arrangement and removed the background.
Our research focuses on a single crop species: potatoes, which comprise a class of healthy photos and two disease classes: early and late blight. The application of a targeted methodology enhances the coherence and precision of the analysis, hence increasing the importance and feasibility of the research findings.

B. Preprocessing of Data

The preprocessing pipeline is a set of operations shown in Fig. 1 intended to improve the data prior to training the detection model. The methods are described in brief.
a) **Image Frame Extraction**: It is the process of identifying and extracting individual frames from a video sequence. This technique is commonly used in various fields, including computer vision, video processing, and multimedia applications. Extracting frames from a video allows for detailed analysis of each frame independently, enabling tasks such as object detection, tracking, and recognition.
b) **Data Labeling**: It is the process of allocate relevant tags to crude data, as a rule in the context of machine learning and artificial intelligence. This labeling is crucial for training and validating machine learning models, as it provides the ground truth or correct output that the model aims to learn from. In particular, each image was painstakingly manually annotated to identify illnesses on individual leaves using the web platform **RoboFlow.**
c) **Data Augmentation**: The technique of "data augmentation," which creates new data points from an existing dataset, is used to remedy this. As a countermeasure against overfitting, this may entail making minor adjustments to the current data or using machine learning techniques to generate brand-new data points. The data augmentation techniques used in this investigation is image rotation, flipping, brightness, and exposure adjustment.
d) **Data Resizing**: It refers to the process of adjusting the dimensions of data, typically images, to a desired size. This technique is commonly used in various fields including computer vision, image processing, and ML to prepare data for analysis, visualization, or model training.
.

C. YOLOv8n Model

The preprocessed data is utilized to train the model known as YOLOv8n, which is the subject of this work. The eighth version of this model, known as YOLOv8n, or You Only Look Once with nano architecture, is famous for its remarkable real-time object identification abilities. The YOLOv8n model's design includes a CSPDarknet53 feature extractor in its backbone. This part efficiently collects important information from the input photos, which is then applied to object detection tasks.

The C2f module is an innovative module that replaces the traditional YOLO neck architecture after the feature extractor. It is possible that this C2f module is essential to the model's ability to do extra object detection tasks. Notably, YOLOv8 forecasts an object's placement central point directly instead of having to subtract it from a pre-decided anchor box. This is because the model functions as an anchor-free model. This drastically lowers the quantity of box predictions, which accelerates the difficult Non-Maximum Suppression (NMS) post-processing step.

YOLOv8n's end-to-end training and application in leaf disease detection are motivated by a number of significant benefits. With faster and more accurate performance than its predecessors, it offers cutting-edge functionality. Plant disease diagnosis and classification depend on picture classification, object detection, and instance segmentation, all of which are supported by its cohesive architecture across a wide range of computer vision AI tasks. Moreover, YOLOv8's intuitive API and effective training procedure enable simple adaptation for particular datasets, like photo sets of potatoes. Together, these characteristics make YOLOv8n a powerful instrument for identifying leaf diseases in comparison to other tools. Finally, performance evaluation is conducted, and this process is elaborately described in section 3.

3. HARDWARE AND SOFTWARE SETUP AND RESULTS ANALYSIS

A. Image Dataset

The PlantVillage dataset, which is accessible online, was utilized to construct the dataset for this study. This dataset includes one type of plant, two different disease classes with varying sizes, shapes, and textures, and a third class of healthy plants. Each disease class comprises 1000 photographs, while the healthy class consists of 152 images. Thus, there are a total of 2000 disease-related images and 152 healthy images. Table I presents a summary of all the data instances employed in this investigation, both before and after employing data augmentation. We created training, validation, and a testing set from this dataset. A train-to-test ratio of 80:10:10 was used to split the data, with 10% going toward testing, 80% going toward training, and 10% going toward validation.

Table I: PRE- AND POST- AUGMENTATION IMAGES

Dataset	Pre-Augmentation	Post-Augmentation
PlantVillage	2152	5238
Train Set	80%	4583
Validation Set	10%	437
Test Set	10%	218

After argumentation train, validation, and test set becomes 88%, 8%, and 4%.

Figures 2 and 3 display the input data histogram versus the labels. Your image's labels are in xywh space.

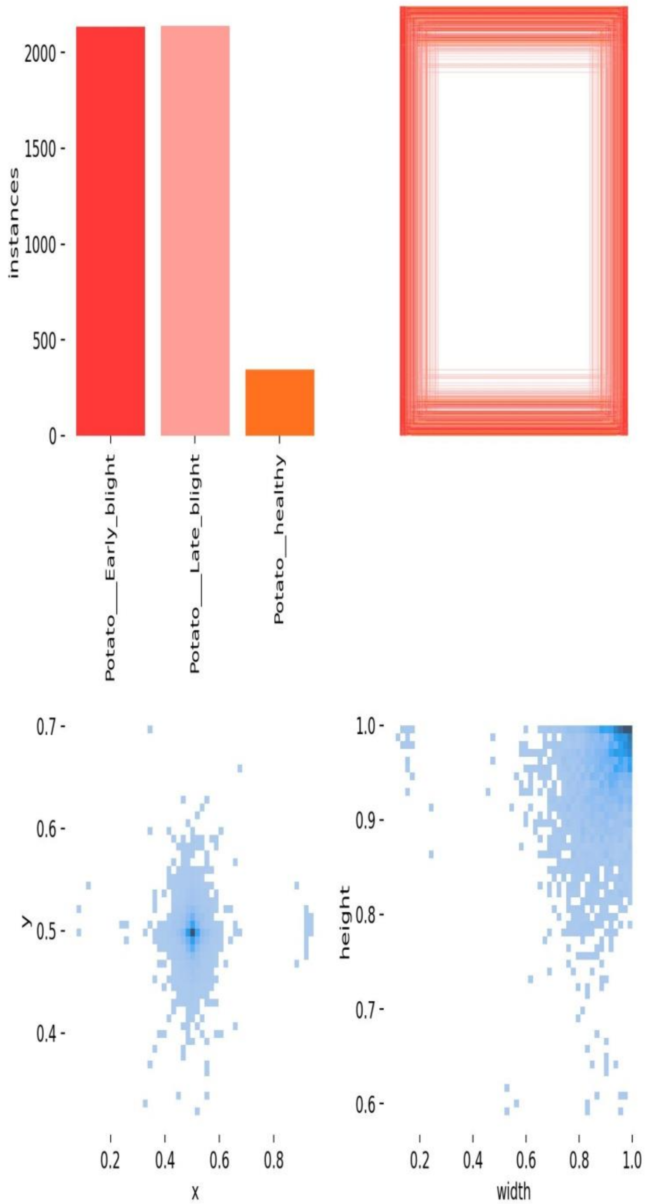

Fig. 2 labels

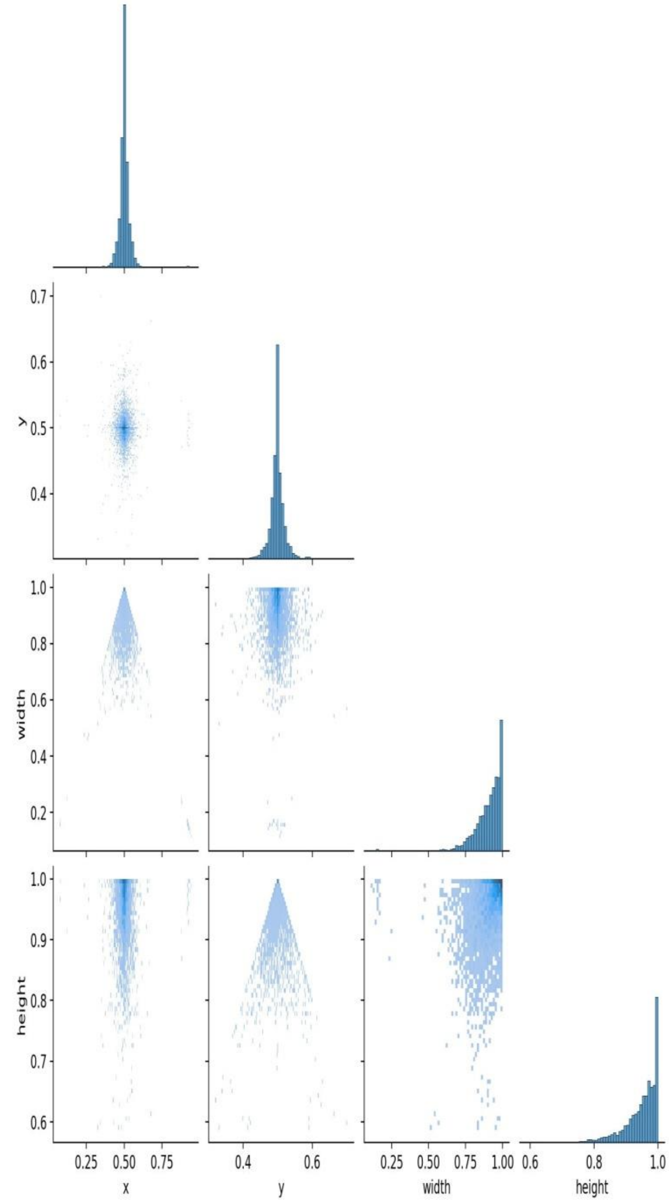

Fig. 3 labels_correlogram

Correlation statistics, or Lables_Correlogram, is a collection of two-dimensional histograms that show the relationship between each axis of your data. The distribution of the discriminative components is essentially normal, as can be seen in the histograms at the top of the x and y columns. This feature gives the detection model more flexibility in identifying discriminative portions. Patch (x, y) shows that the components that were found cover every aspect of detecting potato leaf disease.

It is clear by analyzing patch (x, width) and patch (y, height) that the local components are distributed uniformly along both axes, despite a small ratio of less than 1.0. Patch (width, height) shows that almost every component only covers a small portion of the overall image.

B. Hardware and Software Setup

The hardware and software setup is detailed in Table II.

Table.2 Hardware and software setup

CPU	CPU (Intel Core(TM) i5-6200U 2.30GHz)
GPU	0
RAM	24 GB
OS	Windows 11
SOFTWARE	Ultralytics YOLOv8.0.145 Python-3.9.12 torch-2.0.1

For training the model, the following hyperparameters were employed: epochs=5, workers=8, size of batch=16, and size of image is 640 x 640 pixels.

C. Results Analysis

The YOLOv8n network was employed to train plants in detecting leaf diseases. The usefulness of the constructed method is manifested through tables and graphs, showcasing various metrics that describe the model's performance on both the training as well as validation sets.

A performance evaluation of the model is shown in Table III, which covers 5 epochs of metrics for both the bounding box detection and classification tasks.

Table. 3 The model gains the following matrix after 0 to 4 epochs:

epoch	4
train/box_loss	0.50173
train/cls_loss	0.46554
train/dfl_loss	1.1732
val/box_loss	0.48556
val/cls_loss	0.3916
val/dfl_loss	1.2383
metrics/precision(B)	0.9457
metrics/recall(B)	0.94164
metrics/mAP50(B)	0.97297
metrics/mAP50-95(B)	0.86776
lr/pg0	0.00058017
lr/pg1	0.00058017
lr/pg2	0.00058017

• train and val in terms of box loss: These measures quantify the bounding box regression's loss. In the validation and training sets, they quantify the difference between the predicted bounding boxes and the real ground truth bounding boxes, respectively.

• train and val for the CLS loss: These measurements show the amount of loss experienced throughout the classifying process. They evaluate the accuracy of the model in predicting the right label for a particular image.

• During training and validation for the DFL loss, which stands for Distribution Fitting Loss, this method is employed to fine-tune boundaries. The objective is to enhance the localization of object boundaries, particularly crucial for accurately delineating affected areas.

• metrics/precision(B), metrics/recall(B): In ML, precision and recall are essential measures. We can determine what percentage of the negative class was correctly identified by looking at precision, specificity, or true negative rate. Recall is the percentage of all pertinent instances that have been successfully redeemed, whereas precision is the percentage of pertinent instances among those that have been recovered. The percentage of the positive class that was correctly classified is indicated by recall, sensitivity, or true positive rate.
Subscripts 'B' may represent particular classes or categories in the dataset.

• mean Average Precision (mAP50 and mAP50-95): t is the test picture or query, and mAP is the average precision of each label. According to Equation 1, *T* is the number of test samples. IOUs (Intersection over Union) are employed for this purpose, and mAP50 is the accuracy when IOU=50, meaning that if there is more than 50% overlap, the detection is successful. mAP50-95, between 0.5 and 0.95, step 0.05, across various IOU thresholds (0.5, 0.55, 0.6, 0.65, 0.7, 0.75, 0.8, 0.85, 0.9, 0.95).
Equation. 1

$$mAP := \sum_{i=1}^{T} AP(t_i)/T$$

• The model was trained using 640 x 640 photos, a batch size: 16, and learning rate: 0.00058017 over the course of 5 epochs.

The outcomes demonstrate the model's performance across five epochs in identifying object-over-leaf illnesses. With a precision of 94.57% in bounding box detection, the model exhibits high accuracy in locating and identifying objects of interest. Moreover, achieving a recall of 94.164% in bounding box detection indicates the model's strong sensitivity in identifying unhealthy areas requiring detection. This combination of enhanced recall and precision yields an splendid F1 score of 94.367%, underscoring the model's remarkable capability in recognizing and delineating illness regions in the images.

The accompanying Fig. 4 shows these graphic representations of the Precision, Recall, Precision-Recall, and F1-Score curve. The average precision (AP) is measured in the region below the precision-recall curve (Equation 2).

$$\text{Average Precision(AP)} = \int_0^1 \text{P(R)dR}$$

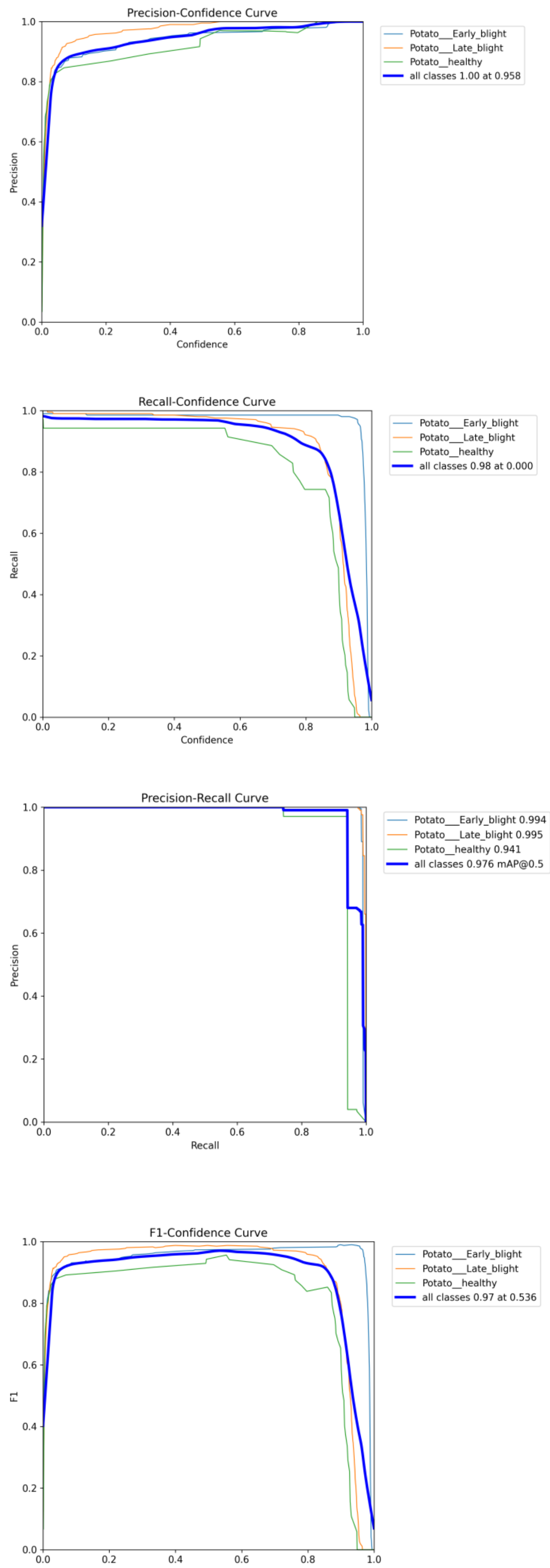

Fig.4 Precision, Recall, Precision-Recall, and F1-Score curve

Fig. 5 and Fig. 6 depict confusion matrix and the normalized confusion matrix. The model achieved an overall accuracy of roughly 97.025 %.

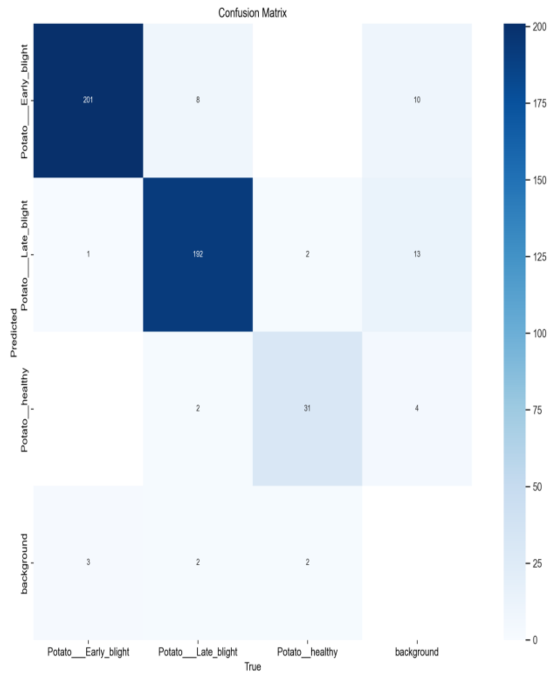

Fig.5 confusion matrix

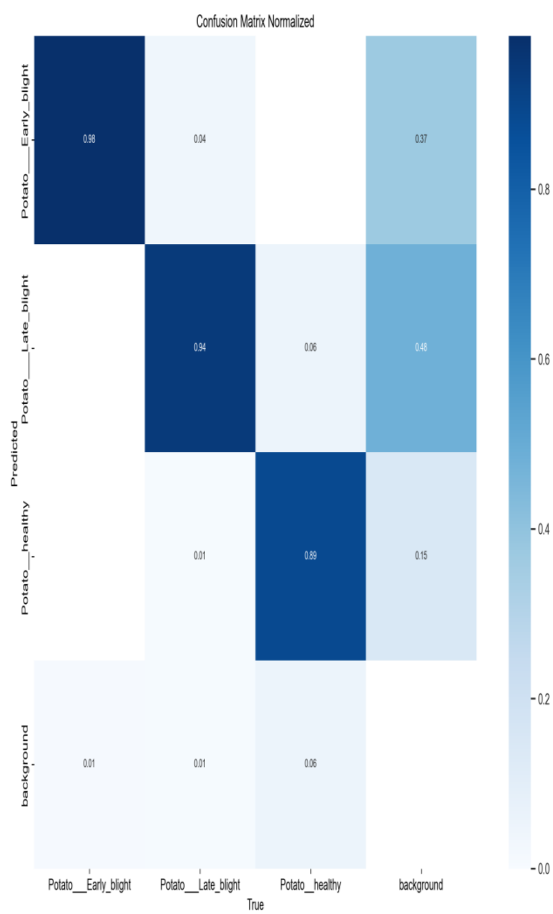

Fig.6 normalized confusion matrix

Figs. 7 and 8 show the validation results of visualizing leaf disease detection and categorization. These pictures clearly show how YOLOv8n creates precise bounding boxes and classification jobs, making it possible to identify and categorize sick leaves with accuracy.

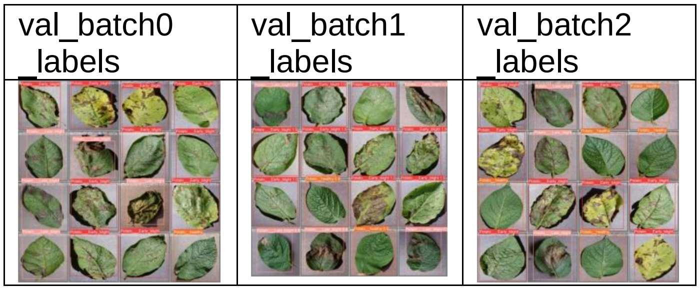

Fig. 7 Leaf Disease Detection using YOLOv8n (labels)

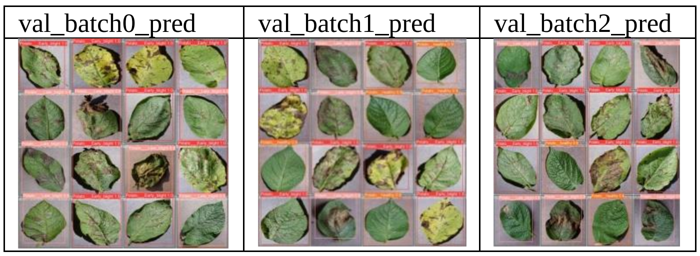

Fig. 8 Leaf Disease Detection using YOLOv8n (predictions)

These striking results support the agility of the YOLOv8n object detection model used in this investigation. The higher scores showcase how well the YOLOv8n model performs in challenging tasks like classifying and detecting leaf diseases. This demonstrates how well it manages the trade-offs between recall and precision, resulting in exceptional F1 scores for both categorize prediction and bounding box detection. The model is a powerful tool in the field of agriculture and plant leaf disease handling because of its reliable and accurate performance in these conditions.

We thoroughly assessed our suggested strategy by comparing it to the most advanced techniques available in the industry. The comparison's results are furnished in Table IV, where key performance metrics and metrics that our YOLOv8n model for plant disease spotting and classification achieved are highlighted. This thorough research provides priceless insights into the development and effectiveness of the YOLOv8n model from start to finish.

Table 4. Analyzation

Author	Model	Diseases	Results %
[23]	Improved YOLOv5	1. Tea cell eater 2. Leaf blight	Detection Accuracy: 91 Precision: 87.80 Recall: 85.27
[24]	YOLOv7	1. Red Spider 2. Tea mosquito 3. Black rot 4. Brown blight 5. Leaf rust	Detection Accuracy: 97.3 Precision: 96.70 Recall: 96.40 mAP: 98.2 F1-score: 96.5
[25]	YOLOv8n	1. maize Blight 2. Sugarcane Mosaic virus 3. Leaf Spot	Prediction: 99.04 Recall: 87.66 mAP: 99..0
Present Study	YOLOv8n	1. Potato Early Blight 2. Potato Late Blight	Detection Accuracy: 97.025 **For Box:** Precision (P): 94.57 Recall (R): 94.164 F1 score: 94.367 mAP50: 97.297 mAP50-95: 86.776

4. CONCLUSION

The application of deep learning technology has revolutionized the identification of leaf diseases and given farmers the ability to proactively protect their crops from any hazards. In this study, YOLOv8n is implemented for potato leaf detection and classification. Furthermore, we have located diseases in leaf for helping farmers to drip chemical in order to reduce disease in particular location of the leaf. Model's performance is evaluated based on the metrics such confusion matrix, precision, recall, F-1 score, and mean Average Precision (mAP). Augmentation strategies are used to alleviate overfitting-related issues. The illness identification process uses the end-to-end YOLOv8n model, which achieves an outstanding overall detection accuracy of about 97.025%. Therefore, this model can effectively be used for weed detection, finding road condition, traffic control and more.

The novelty of this study lies in proposing a deep learning-based method for timely potato leaf disease detection using the Ultralytics YOLOv8n model. This approach, evaluated with high-performance metrics, enables detection using handheld devices like mobile phones or IoT devices, with broader implications for precision farming and crop management. Overall, this research contributes to advancing agricultural productivity and economic sustainability through efficient disease management strategies.

The YOLOv8n model's potency and effectiveness in handling complicated tasks like leaf disease detection and classification are vividly illustrated by the elevated performance scores in bounding box detection and classification metrics. The model is a powerful tool for plant disease management and precision agriculture because of its accurate and reliable performance in a variety of settings. As with any model, it is imperative to evaluate its performance in real-world scenarios and adjust it in light of fresh and incoming data, even with these encouraging results.

While algorithms in YOLO family have remarkable achievements for detection and classification and localization problems, they have some limitations such they may struggle with accurately detecting small objects in images due to their single-shot detection approach and the limitations of the anchor boxes used in their architecture. Small objects may not be adequately represented by the default anchor boxes, leading to lower detection accuracy. Another limitation is that they may not capture as much fine-grained detail as some other object detection architectures, which can affect their ability to detect intricate objects or subtle features, especially in cluttered or complex scenes.

In our upcoming research endeavors, we aim to develop a tool capable of identifying various types of leaf diseases while integrating additional algorithms to enhance the model's performance. This advancement will empower farmers in the agricultural sector to promptly recognize specific diseases, enabling them to take timely and appropriate actions.

REFERENCES

[1] Hazra, S., Karforma, S., Bandyopadhyay, A., Chakraborty, S., & Chakraborty, D. (2023b). Prediction of Crop Yield Using Machine Learning Approaches for Agricultural Data. *TechRxiv. Preprint.*, 0–10. https://doi.org/10.36227/techrxiv.23694867.v1

[2] Hazra, S., Karforma, S., Bandyopadhyay, A., Chakraborty, S., & Chakraborty, D. (2023a). *Machine Learning Techniques For Crop Yield Prediction* (pp. 0–10). https://doi.org/10.53555/sfs.v10i1S.2319

[3] Chakraborty, S., & Newton, A. C. (2011). Climate change, plant diseases and food security: an overview. *Plant Pathology*, *60*(1), 2–14. https://doi.org/10.1111/j.1365-3059.2010.02411.x

[4] Voulodimos, A., Doulamis, N., Doulamis, A., & Protopapadakis, E. (2018). Deep learning for computer vision: A brief review. *Computational Intelligence and Neuroscience*, *2018*. https://doi.org/10.1155/2018/7068349

[5] Jha, S. B., & Babiceanu, R. F. (2023). Deep CNN-based visual defect detection: Survey of current literature. *Computers in Industry*, *148*, 103911. https://doi.org/10.1016/j.compind.2023.103911

[6] Chai, J., Zeng, H., Li, A., & Ngai, E. W. T. (2021). Deep learning in computer vision: A critical review of emerging techniques and application scenarios. *Machine Learning with Applications*, *6*, 100134. https://doi.org/10.1016/j.mlwa.2021.100134

[7] Qadri, S. A. A., Huang, N.-F., Wani, T. M., & Bhat, S. A. (2023). Plant Disease Detection and Segmentation using End-to-End YOLOv8: A Comprehensive Approach. *2023 IEEE 13th International Conference on Control System, Computing and Engineering (ICCSCE)*, 155–160. https://doi.org/10.1109/iccsce58721.2023.10237169

[8] Tseng, K.-K., Lin, J., Chen, C.-M., & Hassan, M. M. (2021). A fast instance segmentation with one-stage multi-task deep neural network for autonomous driving. *Computers & Electrical Engineering*, *93*, 107194. https://doi.org/10.1016/j.compeleceng.2021.107194

[9] Pham, M.-T., Courtrai, L., Friguet, C., Lefèvre, S., & Baussard, A. (2020). YOLO-Fine: One-stage detector of small objects under various backgrounds in remote sensing images. *Remote Sensing*, *12*(15), 2501. https://doi.org/10.3390/rs12152501

[10] Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: Unified, real-time object detection. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 779–788. https://doi.org/10.1109/cvpr.2016.91

[11] Redmon, J., & Farhadi, A. (2018). Yolov3: An incremental improvement. *ArXiv Preprint ArXiv:1804.02767*. https://doi.org/10.48550/arXiv.1804.02767

[12] Bochkovskiy, A., Wang, C.-Y., & Liao, H.-Y. M. (2020). Yolov4: Optimal speed and accuracy of object detection. *ArXiv Preprint ArXiv:2004.10934*. https://doi.org/10.48550/arXiv.2004.10934

[13] Jocher, G., Stoken, A., Borovec, J., Changyu, L., Hogan, A., Diaconu, L., Poznanski, J., Yu, L., Rai, P., & Ferriday, R. (2020). ultralytics/yolov5: v3. 0. *Zenodo*. https://doi.org/10.5281/zenodo.3983579

[14] Kang, C. H., & Kim, S. Y. (2023). Real-time object detection and segmentation technology: an analysis of the YOLO algorithm. *JMST Advances*, 1–8. https://doi.org/10.1007/s42791-023-00049-7

[15] Wang, C.-Y., Bochkovskiy, A., & Liao, H.-Y. M. (2023). YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 7464–7475. https://doi.org/10.48550/arXiv.2207.02696

[16] Terven, J., & Cordova-Esparza, D. (2023). *A Comprehensive Review of YOLO: From YOLOv1 and Beyond*. 1–34. http://arxiv.org/abs/2304.00501

[17] Islam, M., Dinh, A. Van, Wahid, K. A., & Bhowmik, P. (2017). Detection of potato diseases using image segmentation and multiclass support vector machine. *2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE)*, 1–4. https://api.semanticscholar.org/CorpusID:6339549

[18] Samajpati, B. J., & Degadwala, S. (2016). Hybrid approach for apple fruit diseases detection and classification using random forest classifier. *2016 International Conference on Communication and Signal Processing (ICCSP)*, 1015–1019. https://api.semanticscholar.org/CorpusID:10236950

[19] Afzaal, H., Farooque, A. A., Schumann, A. W., Hussain, N., McKenzie-Gopsill, A., Esau, T., Abbas, F., & Acharya, B. (2021). Detection of a Potato Disease (Early Blight) Using Artificial Intelligence. *Remote Sensing*, *13*(3). https://doi.org/10.3390/rs13030411

[20] Chakraborty, K. K., Mukherjee, R., Chakroborty, C., & Bora, K. (2022). Automated recognition of optical image based potato leaf blight diseases using deep learning. *Physiological and Molecular Plant Pathology*, *117*, 101781. https://doi.org/10.1016/j.pmpp.2021.101781

[21] Chen, W., Chen, J., Zeb, A., Yang, S., & Zhang, D. (2022). Mobile convolution neural network for the recognition of potato leaf disease images. *Multimedia Tools and Applications*, *81*(15), 20797–20816. https://doi.org/10.1007/s11042-022-12620-w

[22] Hughes, D., & Salathé, M. (2015). An open access repository of images on plant health to enable the development of mobile disease diagnostics. *ArXiv Preprint ArXiv:1511.08060*. https://doi.org/10.48550/arXiv.1511.08060

[23] Lin, J., Bai, D., Xu, R., & Lin, H. (2023). TSBA-YOLO: An improved tea diseases detection model based on attention mechanisms and feature fusion. *Forests*, *14*(3), 619. https://doi.org/10.3390/f14030619

[24] Soeb, M. J. A., Jubayer, M. F., Tarin, T. A., Al Mamun, M. R., Ruhad, F. M., Parven, A., Mubarak, N. M., Karri, S. L., & Meftaul, I. M. (2023). Tea leaf disease detection and identification based on YOLOv7 (YOLO-T). *Scientific Reports*, *13*(1), 6078. https://doi.org/10.1038/s41598-023-33270-4

[25] Khan, F., Zafar, N., Tahir, M. N., Aqib, M., Waheed, H., & Haroon, Z. (2023). A mobile-based system for maize plant leaf disease detection and classification using deep learning. *Frontiers in Plant Science*, *14*, 1079366. https://doi.org/10.3389/fpls.2023.1079366

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