Potato Crop Disease Classification using YOLOv7 Framework

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Abstract. Crop diseases are a major challenge that can significantly affect agricultural productivity and profitability. The traditional ways adopted by farmers for detecting and classifying these diseases are time-consuming and require huge resources. There have been few attempts to classify the crop diseases using Deep Learning methods such as Mask R-CNN, YOLOv3, Faster R-CNN, and Retina_UNET_Ag etc. But these methods achieve low accuracies in practice.
This paper aims to work on improving the accuracies so that the model can be used for public use with high confidence. In this paper, we propose to use YOLOv7 framework for object detection and classification for the publicly available potato crop Unmanned Aerial Vehicle (UAV) dataset. The proposed framework achieves 94% mAP@.5:.95 for all the disease classes.

Keywords: Crop diseases Classification · Unmanned Aerial Vehicle Images · VOLOv7 · Deep learning.

1 Introduction

The Food and Agriculture Organization (FAO) of the United Nations has projected that the world's population will reach 9.7 billion by 2050, necessitating a significant increase in food production to ensure adequate food supply for all. The FAO also approximates that agricultural crop yields will need to increase by about 70 percent to meet the demands of the growing population [1]. The potato is one of the most important food crops in the world, ranking as the fourth-largest crop after maize, wheat, and rice. It serves as a crucial source of food security for millions of individuals globally. The potato is not only a staple food in many countries, but it is also an important economic crop that significantly contributes to the economies of many nations. The International Potato Center (CIP) estimates that globally, potato losses due to pests and diseases can range from 10 to 30 percent annually, with losses as high as 100 in some cases. These losses are exceptionally high in developing countries, where access to crop protection technologies and resources is limited.

Potato crop production relies on timely and accurate disease diagnosis to ensure sustainable crop production and global food security. Disease detection methods primarily involve visual inspections conducted by trained farmers or experts[2]. However, these methods are often unreliable, time-consuming, and expensive. Farmers may lack the necessary training and knowledge to accurately identify the cause of plant symptoms, and personal biases or environmental conditions can influence their observations. Moreover, identifying diseases in large fields can be challenging, and the accuracy of disease identification can vary based on the expertise of the person conducting the inspection[3]. Therefore, there is a critical need to develop more automated and objective approaches for rapidly and reliably detecting diseases. These approaches should detect diseases early, enabling effective prevention and intervention before they spread uncontrollably. This can reduce the excessive use of pesticides and herbicide treatments.

In recent years, there has been significant progress in Artificial Intelligence (AI) and Unmanned Aerial Vehicles (UAVss). The combination of UAVss and deep learning technology has dramatically advanced the field of agriculture, providing new opportunities for agricultural applications. Over the past few years, several studies [7–9] have utilized different types of data, including RGB (red, green, blue), multispectral, hyperspectral, and thermal infrared data, obtained through the application of UAVs and deep learning technology. These studies aimed to evaluate the phenotypic characteristics of crops [10], identify essential features of plants and plant leaves [11], analyze stressed and healthy, and detect plant diseases[12, 13]. Plant disease diagnosis is one of the significant applications of deep learning and UAVs in agriculture. The images captured by UAVss can be processed using deep learning algorithms, such as convolutional neural networks (CNNs), to detect and classify plant diseases accurately. This automation process could offer solutions to farmers and the wider population where there is a lack of experts to accurately identify different types of disease at a very early stage. Subsequently, farmers can prevent the spread of the disease and minimize crop losses.

Our study presents a framework for promptly identifying and categorizing diseases in potato crops through deep learning techniques and a dataset of UAVs images collected during an actual scenario. Rather than focusing solely on high-quality photos, which may not be easily accessible in regions with limited technological advancements, we aim to establish and implement a model that can yield accurate outcomes even when the images are of poor quality or appearance. We added the image enhancement technique to improve the visual quality of UAVs-captured images.

Figure 1 depicts the proposed framework for identifying healthy and stressed potato crops using image enhancement and object detection techniques. The framework consists of two main steps. In the first step, an image enhancement technique called Relative Global Histogram Stretching (RGHS) [6] is used to improve the image quality and prepare the data for object detection. In the second step, a deep learning object detection network called YOLOv7 is utilized to identify and classify potato crops as either healthy or stressed. Overall, the framework aims to achieve optimal performance by combining these two techniques in a two-step process.

Fig. 1. Proposed framework for identifying healthy and stressed potato crops using image enhancement and object detection techniques. The framework consists of two main steps: image enhancement and deep learning object detection and classification network. The model identifies and classify potato crops as either healthy or stressed.

This research evaluates YOLOv7 performance for disease detection and classification of potato crops using UAVs data. The primary contributions of this study include:

1. We implemented YOLOv7 for real-time disease detection and classification for potato crops on the dataset of UAVs images collected during an actual scenario.

2. We improved the visual quality of UAVs images collected during an actual scenario using digital image enhancement techniques.

3. We explored and assessed the effectiveness of a YOLOv7 object detector model in identifying and detecting diseases in potato crops over original and enhanced dataset.

The article is structured as follows: Section 2 focuses on related studies relevant to the current work, while Section 3 details the materials and methods used in the research. The experimental setup and performance evaluation of the proposed method are discussed in Section 4. Finally, Section 5 offers concluding remarks and suggestions for future research.

2 Related Works

Combining unmanned aerial vehicles (UAVs) and Deep learning can aid in diagnosing plant diseases. The process involves data acquisition through high-resolution camera images, data preprocessing to enhance image quality, image analysis using deep learning algorithms to identify disease symptoms and predict outbreaks, disease diagnosis, and monitoring and feedback to assess control measures' effectiveness. This approach can efficiently detect and prevent disease outbreaks, improving crop yields and reducing environmental impact. This section discussed related studies relevant to the current work in deep learning, unmanned aerial vehicles (UAVs), and agriculture.

Potato crop stress identification and disease detection have become essential research topics recently. Various studies have been conducted using machine learning and deep learning-based methods to classify and detect different types of stress and diseases in potato crops. For instance, in [4], deep neural networks were used to analyze aerial images of potato crops to demonstrate automated spatial recognition of healthy versus stressed crops. Similarly, in [14], a Convolutional neural network (CNN)-based Deep learning (DL) multi-classification model was developed to categorize images of potato crop plants with healthy and potato blight (PB) disease images based on their PB disease severity level.

In [15], the authors used the convolution neural network (CNN) method to examine 5 classes of potato diseases, including Healthy, Black Scurf, Common Scab, Black Leg, and Pink Rot. The results of potato defect classification methods were compared with other methods such as Alexnet, Googlenet, VGG, R-CNN, and Transfer Learning. The authors of [2] developed a multi-level deep learning model using the YOLOv5 image segmentation method to recognize potato leaf disease. Furthermore, [16] proposed a technique that acknowledges strange plants or leaves based on the growth stage, and [17] used spectroscopy for potato disease management.

In addition to potato crops, Unmanned Aerial Vehicles (UAVss) can be used for crop detection in various other applications. For instance, [18] proposed a technique to determine the optimal flight path for UAVss to gather data using sensors. Similarly, in [19], satellite/UAVs data fusion and machine learning combined canopy spectral data with canopy structure features for crop monitoring. [20] classified sugar beet fields using a CNN-based Weednet framework for aerial multi-spectral images of sugar beet fields. In [21], the authors presented literature on sensors, crop monitoring by UAVs, types of vehicles, identifying specific applications, and image processing techniques. Furthermore, [22] monitored rice crops using multirotor UAVs and RGB digital cameras, and [23] predicted the yield of corn crop through height estimation generated by a 3D photogrammetry using UAVs.

YOLOv7 has also been used for crop detection in various applications. For example, in [24], deep object detection of crop weeds was performed using YOLOv7 on a real case dataset from UAVs images. Similarly, in [25], YOLOv7 combined with data augmentation was used to detect Camellia oleifera Fruit in Complex Scenes. In [26], a new high-precision and real-time method called Maize-YOLO was created for maize pest detection. Other applications of YOLOv7 include hand recognition [27] and the detection and classification of damaged roads [28].

3 MATERIALS AND METHODS

3.1 UAVs dataset acquisition

The dataset used in this paper is collected by Aleksandar Vakanski et al. [4], which is available for open public access.To acquire the UAVs dataset, Aleksandar Vakanski et al. [4] conducted a study on a 4.3-acre potato field planted with 'Russet Burbank' potatoes at the University of Idaho - Aberdeen Research and Extension Center in Bingham County, Idaho. The plants were overhead irrigated and fertilized according to recommendations for southeast Idaho. However, plants along the first five rows along the field's western edge experienced up to a 50% reduction in water inputs compared to the rest of the area, leading to drought stress. The field was assessed for diseases and nutrient levels to confirm that the observed stress was due to a lack of water. Plants were evaluated on August 13, 2018, when stressed plants started to senesce prematurely. A small UAVs Solo by 3DR was used to collect aerial images of a field, with a multispectral camera Sequoia by Parrot mounted on it. The Sequoia camera has an integrated RGB camera with 16 MPx resolution (3,456×4,608 pixels). The drone was flown at an altitude of 3 meters and a slow speed of 0.5 m/s, with a ground resolution of 0.08 cm for the RGB sensor. A time-lapse mode was used to capture the images with a time interval of 1.21 seconds.

3.2 Potato Crop Disease Dataset

We obtained a potato crop disease dataset from open public access repository (data source: `https://www.webpages.uidaho.edu/vakanski/Multispectral_Images_Dataset.html`, last accessed on 15 March 2023). This dataset consists of 1,560 (actual images and augmented images) images. Each image has a size of 750×750×3 and bounding box labels containing a mix of healthy and stressed potato plants(in XML and CSV format). The detailed information on the dataset is listed in Table 1.

Table 1. Detailed information on the obtained potato crop disease dataset

Files	Infromation
Train_Images	1500 RGB images (750×750 each)
Test_Images	60 RGB images (750×750 each)
Train_Labels_CSV	Bounding box annotations of 1500 images
Test_Labels_CSV	Bounding box annotations of 60 images
Train_Labels_XML	Bounding box annotations of 1500 images
Test_Labels_XML	Bounding box annotations of 60 images

Two samples of field images of potato plants are shown in Figure 2. The left image shows a group of plants with varying shades of green, while the right image shows another group with a similar appearance. However, in both images, there is a clear distinction between healthy and stressed plants. In the left image, the stressed plants are located in the upper half segment, which appears to have a yellowish tint and less foliage compared to the healthy plants in the lower-half segment of the image. Similarly, in the right image, the stressed plants are located in the right-half segment, which also appears to have a yellowish tint and less foliage than the healthy plants in the left-half segment of the image.

Fig. 2. The figure shows two high-resolution field images of potato plants, clearly distinguishing between healthy and stressed plants. The left image has stressed plants in the upper-half segment and healthy plants in the lower-half segment, while the right image has stressed plants in the right-half segment and healthy plants in the left-half segment.

3.3 Relative Global Histogram Stretching (RGHS)

In 2018, Huang et al. proposed a method called relative global histogram stretching (RGHS)[6] that can improve the visual effect of images by considering the distribution characteristics of RGB channels. The technique employs adaptive histogram stretching in the RGB color model and linear and curve adaptive stretching optimization in the CIE-Lab color space. RGHS avoids blind enhancement and retains available information, improving the image's visual effect. The following equation represents the RGHS method:

$$P_{out} = (P_{in} - I_{min})(\frac{(O_{max} - O_{min})}{(I_{max} - I_{min})}) + O_{min} \tag{1}$$

In this equation, P_{out} is the output pixel value, P_{in} is the input pixel value, I_{max} and I_{min}) are the maximum and minimum values of the input range. O_{max} and O_{min}) are the maximum and minimum values of the output range. The equation linearly scales and shifts the pixel values from the input range to the output range, considering the image's specific characteristics. This helps to avoid over-stretching or under-stretching of particular color channels and preserves the details of the original image while improving its visual quality.

3.4 YOLOv7

YOLOv7[5] is a recently released object detection model that achieves highly enhanced and accurate performance without increasing computational and inference costs. It outperforms other object detectors by reducing about 40% of the parameters and 50% of the computation required for state-of-the-art real-time object detection, allowing it to perform inferences more quickly with higher detection accuracy. YOLOv7 uses a more efficient feature integration approach, a more stable loss function, and optimized label and model training efficiency. It requires less expensive computational hardware and can be trained more quickly on small datasets without using pre-trained weights. YOLOv7 is a single-stage object detector with a backbone for feature extraction, a neck for generating feature pyramids, and a head for performing the final detection as an output. Compared to previous YOLO versions, the authors in [5] introduced many architectural changes in YOLOv7, which include compound model scaling, (EELAN) extended efficient layer aggregation network and trainable bag of freebies for more efficient training.

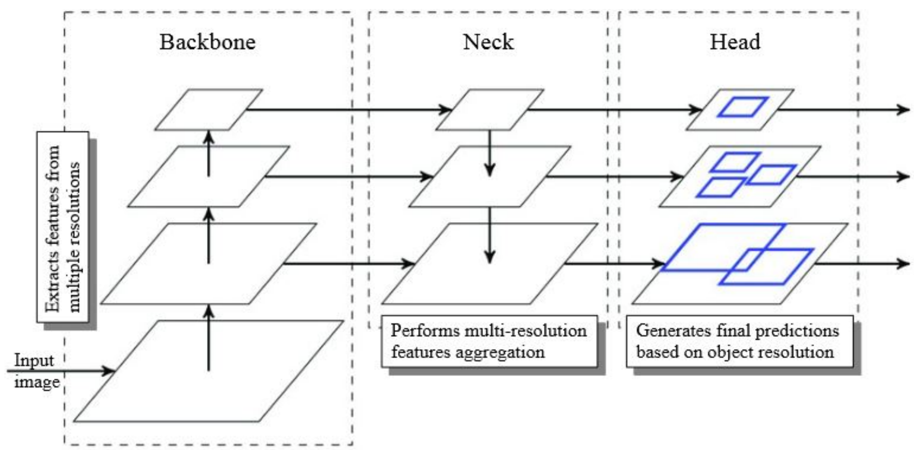

Fig. 3. YOLOv7 is a single-stage object detector with a backbone for feature extraction, a neck for generating feature pyramids, and a head for performing the final detection as an output.

Extended Efficient Layer Aggregation Network: The YOLOv7 backbone incorporates a computational block known as E-ELAN, which stands for Extended Efficient Layer Aggregation Network. This architecture utilizes "expand, shuffle, merge cardinality" to enhance the model's learning capabilities. By doing so, the network can continuously improve its learning ability without disrupting the original gradient path. Apart from preserving the original ELAN design architecture, E-ELAN can also direct distinct sets of computational blocks to acquire a broader range of features during the learning process.

Compound Model Scaling: Model scaling adjusts key attributes of a model to meet different application requirements. These include model width, depth, and resolution. In traditional concatenation-based architectures, scaling factors cannot be analyzed independently, but YOLOv7 introduces compound model scaling to maintain the optimal structure while adjusting these attributes. This approach allows for the independent scaling of different factors and preserves the original design properties of the model.

Planned Reparameterized Convolution: Reparameterization is a method that improves the model after training, leading to better inference outcomes. Two types of reparameterization are used: model-level and module-level ensembles. YOLOv7 uses RepConvN, a convolutional block similar to Resnet but without an identity connection, in its reparameterized architecture. The authors suggest avoiding identity connections when using a convolutional layer with concatenation or a residual to replace the reparameterized convolution.

Coarseness for Auxiliary Loss and Fineness for Lead Loss The YOLOv7 architecture has multiple heads, with the lead head being responsible for the final output and the auxiliary head aiding in the training process. A two-label assigner process is used, with the lead head-guided label assigner producing soft labels representing the distribution and correlation between the source and target data. The coarse-to-fine lead head-guided label assigner has two sets of soft labels, coarse and fine, using the predicted outcomes of the ground truth with the lead head. The significance of coarse and fine labels can be adjusted dynamically during training.

4 Experimental setup and Results

4.1 Experimental setup

To promptly identify and categorize diseases in potato crops, we used YOLOv7 and a dataset of UAVs images collected during an actual scenario described in previous sections 4.1 and 4,2. We obtained a total of 1540 images which contained 20120 bounding boxes of healthy and stressed classes. (We discarded 20 images from the obtained dataset because of invalid annotations). We partitioned the remaining dataset into the train, validation, and test splits based on deep learning standards, taking approx 80% for the training set, 10% for the validation set, and 10% for the test set. The final dataset splits consist of 1214 training images, 172 validation images, and 154 test images, and we named it the "original" dataset (i.e., without image enhancement). All the original dataset images with the same slits were enhanced using RGHS method. We called this dataset an "enhanced" dataset (i.e., with image enhancement). We evaluate the performance of the YOLOv7 to identify and categorize disease in potato crops over both original and enhanced datasets. The details of the YOLOv7 model with trainable parameters are presented in Table 2.

Table 2. YOLOv7 model trainable parameters tables.

Parameters	**Values**	**Comments**
lr0	0.01	initial learning rate (SGD=1E-2, Adam=1E-3)
lrf	0.1	final OneCycleLR learning rate (lr0 * lrf)
momentum	0.937	SGD momentum/Adam beta1
weight_decay	0.0005	optimizer weight decay 5e-4
warmup_epochs	3.0	warmup epochs (fractions ok)
warmup_momentum	0.8	warmup initial momentum
warmup_bias_lr	0.1	warmup initial bias lr
box	0.05	box loss gain
cls	0.3	cls loss gain
cls_pw	1.0	cls BCELoss positive_weight
obj	0.7	obj loss gain (scale with pixels)
obj_pw	1.0	obj BCELoss positive_weight
iou_t	0.20	IoU training threshold
anchor_t	4.0	anchor-multiple threshold
fl_gamma	0.0	focal loss gamma (efficientDet default gamma=1.5)

The implementations and experimentations of the proposed models were performed on the Python-3.6 environment with TensorFlow-2.4 version. A virtual machine with 40 core processor, 128 GB of RAM, and V100 tesla GPU used as the hardware environment.

4.2 Results

Evaluation Metrics The performance of the proposed framework discussed in this paper is evaluated based on the precision, recall, mAP@.5 and mAP@.5:.95 values are computed for each class included in the dataset. The standard definitions of true positive, false positive, and false negative are utilized within the scope of object detection to determine these values. mAP@.5 and mAP@.5:.95 are commonly used evaluation metrics in object detection. mAP@.5 and mAP@.5:.95 differ in the threshold of intersection over union (IoU) used to define a true positive detection.mAP@.5, also known as AP@0.5 or AP50, calculates the average precision at a single IoU threshold of 0.5. In other words, a predicted bounding box is considered a true positive detection if its IoU with the ground truth bounding box is greater than or equal to 0.5. This metric is widely used in object detection benchmarks, such as the PASCAL VOC and COCO datasets. On the other hand, mAP@.5:.95, also known as AP@.5:.95 or AP75, calculates the average precision over a range of IoU thresholds from 0.5 to 0.95, with a step size of 0.05. This metric considers a predicted bounding box a true positive if its IoU with the ground truth bounding box is greater than or equal to any threshold in the range. This metric is more comprehensive than mAP@.5, considering a range of IoU thresholds and providing a complete picture of the model's performance.

In general, mAP@.5:.95 is a more rigorous metric than mAP@.5, as it evaluates the model's performance across a range of IoU thresholds.

Observations A series of experiments have been conducted to evaluate the efficacy of the proposed framework that utilizes image enhancement and object detection techniques for distinguishing healthy and stressed potato crops. In this series, we have divided the experiments into four possible groups of Original (without enhancement) versus Enhanced Train and Test datasets. These experiments are described as follows:

1. Orignal/ Orignal (OO): Training with Original Data and Testing on Original Data
2. Original/ Enhanced (OE): Training with Original Data and Testing on Enhanced Data
3. Enhanced/ Orignal (EO): Training with Enhanced Data and Testing on Original Data
4. Enhanced/ Enhanced (EE): Training with Enhanced Data and Testing on Enhanced Data

The results with various metrics are presented in Table 3. It can be observed from Table 3 that the proposed framework with EE group of experiments achieve higher recall values for all the cases when compared with OO, OE and EO group of experiments. The EE framework results in similar set of accuracies when compared with all other frameworks. Further, it can be observed that the proposed EE framework attains around 4% of improvement for mAP@.5:.95 over all other frameworks for all the classes.

Figure 4 presents the visual analysis of the ground truth image samples and the prediction results with YOLOv7 framework. Blue edge-labeled image boxes represent healthy crops while yellow edge-labeled image boxes represent stressed crops. The first column of the figure shows the four original RGB image patches collected from the field and labeled with areas of healthy and stressed plants (ground truth). The second column represents an enhanced version of the same four original RGB image patches.

The third column in Figure 4 demonstrates the predicted bounding boxes by YOLOv7, which is trained and tested on the original dataset. The fourth column represents the predicted bounding boxes by YOLOv7, which is trained and tested on the enhanced dataset. Each bounding box's predicted class with confidence level are indicated in the upper left-hand corner of the corresponding boxes in Figure 4. The proposed models recalled the correct bounding boxes of healthy and stressed plants in most of the cases. In Figure 4, the micro details about the bounding boxes, prediction and its confidence can be visualized through Zoom-In. It can be observed from Figure 4 that the confidence level increases after enhancing the images (Fourth Column) in most of the cases. For example, in Figure 4 (Column 3 and 4), the dashed oval section highlights the regions where the confidence level is improved after enhancing the images.

Figure **??** presents the Precision-recall curve for all the frameworks. Figure **??** describes the F1-curve with confidence. In addition, the confusion matrices are presented in Figure **??**. The observations similar to Table 3 can be observed in **??** - **??**. In [4], the authors presented the results on the same dataset that we have used in our experiments, on 1500 training images and 60 testing images using "Retina-UNET-Ag" framework and achieved below 90% accuracy for Precision, Recall, and mAP Healthy and Stressed classes [3].

Table 3. Comparison results with various metrics

(Training data /Testing data)	Class	Precision	Recall	mAP@.5	mAP@.5:.95
Original/Original	All	0.995	0.972	0.989	0.91
	Healthy	0.997	0.971	0.992	0.913
	Stressed	0.992	0.972	0.987	0.907
Original/Enhanced	All	0.972	0.942	0.979	0.837
	Healthy	0.97	0.937	0.98	0.833
	Stressed	0.974	0.947	0.979	0.842
Enhanced/Original	All	0.982	0.96	0.985	0.903
	Healthy	0.986	0.956	0.984	0.904
	Stressed Title	0.979	0.964	0.986	0.902
Enhanced/Enhanced	All	0.987	0.975	0.988	0.942
	Healthy	0.994	0.977	0.992	0.946
	Stressed	0.98	0.973	0.984	0.939

5 Conclusion and Further Work

This study presents YOLOv7 based framework for identifying and categorising the potato crop disease using UAV images. The exhaustive experiments are carried-out to establish the applicability of the proposed framework in real-time deployment. The proposed approach achieves higher mAPs when compared with other variants of the experiments for all the classes.

In future, the authors would like to develop an API for public use for the proposed framework and would also like to explore and compare with various other state-of-the-art approaches in the domain. Further, the proposed method has shown its potential to improve disease detection and classification in potato crops in real-time, leading to more efficient disease management and higher crop yields. This method can also be extended to other crops, providing valuable insights into crop health and disease management.

[3] The code is not available. We could not replicate the results. This is the reason we have not compared it in Table 3.

Fig. 4. The ground truth image samples and YOLOv7's prediction results for healthy and stressed crops. Blue and yellow edge-labeled image boxes indicate healthy and stressed crops, respectively. The figure includes four original RGB image patches and an enhanced version of them in the first and second columns, respectively. The predicted bounding boxes by YOLOv7, trained and tested on both the original and enhanced dataset, are shown in the third and fourth columns, respectively.

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